Mutual Fund Characteristics, Fund Flows, Cash Management and Performance: A Comparative Study Between the China and US Markets

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Abstract

This thesis aims to contribute to the literature on mutual fund markets of China and the US by examining the relative importance of flow determinants, the cash holdings of funds and the performance implications of fund flows. It presents findings from the following three perspectives. By applying Shapley-Owen R-squared decomposition, the first empirical chapter shows that non-risk factors outperform risk factors and risk-adjusted returns in explaining fund flows in both markets. Specifically, investors show more concerns over non-risk factors, including lagged flows, fund size and Morningstar ratings, than risk betas and risk-adjusted alphas in fund selection. In addition, it offers a novel proxy, Smart-to-Dumb Ratio (SDR), which measures the smart money of sophisticated investors. SDR significantly and positively predicts fund performance in the US. The second empirical chapter shows that US fund managers are more influenced by risk factors to determine their cash holdings, while Chinese fund managers are more affected by non-risk factors. Moreover, US fund managers with higher abnormal cash holdings (ACH) are more inclined to tilt their portfolios to lower risk loadings and reduce systematic risk than Chinese fund managers. Furthermore, it shows that abnormal cash holdings attract money inflows in both markets and predict superior fund performance in the US market. The final empirical chapter presents that flow-induced trade (FIT) is significantly and positively associated with stock returns in China, which is consistent with the evidence in the US (Lou, 2012). FIT also significantly and positively predicts short-term fund performance in China. Additionally, it shows that anomaly returns (Stambaugh, Yu and Yuan, 2012) exist and active fund managers may have the ability to exploit stock return anomalies in China.

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Chapter 1 Introduction

1.1 Introduction

Mutual fund investment is a fast-growing trend in modern financial management. Most mutual fund investors seek to earn positive risk-adjusted returns from actively managed mutual funds. When assessing these funds, investors should consider the cost of capital for their investments (Berk and Van Binsbergen, 2016) and evaluate all factors whether they are priced or unpriced (Barber, Huang and Odean, 2016). Scholars initially address the question: what is the decision mechanism of mutual fund investors?

Researchers have studied the decision criteria for investors based on risk-adjusted fund returns in depth. Earlier fund performance measures were developed using asset pricing models with price-level data. These models allow investors to compute the cost of their capital according to different risk factors. The capital asset pricing model (CAPM) describes the linear relationship between the expected return of assets and market risk. The initial development of the CAPM offers investors a perspective to adjust market risk based on fund performance. Jensen (1968) first proposed evaluating risk-adjusted returns using CAPM alpha, which is one of the milestones in the field of asset pricing. Furthermore, the literature developed new risk factors, including size and value risk studied by Fama and French (1993), the momentum factor by Carhart (1997), the investment and the profitability factor by Hou, Xue and Zhang (2014) and Fama and French (2015). If a model can consistently price risks, then mutual investors should use it to adjust fund performance. In recent studies, the CAPM has been found to direct fund flows and outperform other risk models (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016). Since CAPM fails to explain cross-sectional expected returns due to a set of asset pricing anomalies, this raises a question: why is CAPM still dominant in mutual fund pricing? Berk and Van Binsbergen (2016) argue that non-risk factors might offer new insights into possible answers.

To understand the decision criteria of mutual fund investors regarding non-risk factors, a group of studies focus on fundamental fund characteristics. Mutual funds' size erodes their returns (Chen, Hong, Huang and Kubik, 2004; Pollet and Wilson, 2008); mutual investors are aware of fund fees (Barber, Odean and Zheng, 2005; Gil-Bazo and Ruiz-verdu, 2009); a large family size, strong marketing efforts and high media attention can reduce the search cost of funds, and therefore attract money inflows (Sirri and TuFano, 1998). Funds with lower participation costs enjoy higher flow-performance sensitivity among medium-performing funds (Huang, Wei and Yan, 2007). Funds with higher lagged flows tend to outperform their peers subsequently (Zheng, 1999; Keswani and Stolin, 2008). Investors may first employ these variables to allocate their money since they are easily computed and obtained from brokers. This raises a question: how do investors consider these non-risk factors compared to risk factors in their fund decisions?

Further investigations have also been conducted on active management skills in recent literature. They find that active management skills can add value for investors. Pollet and Wilson (2008) show that funds with higher diversification are associated with better performance. This effect is more pronounced in small-cap funds. Cremers and Petajisto (2009) find that funds with more active shares outperform their benchmarks significantly and show strong performance persistence. Kacperczyk, Sialm and Zheng (2005) find that funds with more concentrated investing have better performance. Kacperczyk, Sialm and Zheng (2008) find that return gap reflects the unobserved skills of fund managers and positively predicts fund performance. Kacperczyk and Seru (2007) find that superior fund managers who outperform others normally trade less on public information. Active skills are also significant drivers of mutual fund flows. Investors may also utilize these active measures to identify superior funds.

Given that the literature widely studies the determinants of the mutual fund flows described above, then, to what extent, do investors consider all these priced or unpriced factors in their decisions? However, the relative importance of investor preferences remains largely unexplored. I address the relative importance of fund-flow determinants in the first empirical chapter in both the China and US markets. Common evidence found in these two markets with different investor sophistication makes my findings more robust.

With a first empirical analysis on investor decisions, fund managers can refer to it and adjust their portfolio to accommodate fund flows accordingly. A natural problem arises: how much cash should be retained to maintain liquidity or deal with fund inflows and outflows?

In the second empirical chapter, I focus on fund liquidity management and investigate abnormal cash holdings. Simutin (2013) finds that abnormal cash holdings better predict fund performance in the US. They provide empirical evidence showing that those funds with the highest abnormal cash holdings significantly outperform those funds with the lowest abnormal cash holdings by over 2% annually. Similarly, Graef, Vogt, Vonhoff and Weigert (2018) also confirm the performance predictability of abnormal cash among European funds. Following the literature, I first examine how fund managers determine their cash holdings based on risk and non-risk factors. In addition, Boguth and Simutin (2018) find that constrained mutual fund managers can take advantage of high beta stocks to increase their implicit leverage. Also, Christoffersen and Simutin (2017) find that fund managers have an incentive to maintain low tracking errors for their benchmark by tilting their portfolios towards high-beta stocks. Second, I further study the risk exposure of future investment strategies of funds with higher abnormal cash, the impact of abnormal cash on investor flows, and whether abnormal cash holdings are predictive of fund performance in both China and the US.

Given that investor decision mechanisms and liquidity management have been studied in the first two empirical chapters, does the trade of mutual fund managers motivated by fund flows have performance implications?

In the third empirical analysis, I study flow-induced trading and examine its relation to stock return anomalies. Coval and Stafford (2007) find that mutual funds that experience massive capital outflows may transact its holding at a disadvantage price. Investors profit for providing liquidity from asset fire sales of mutual funds. Similarly, fund managers who have massive money inflows tend to invest more than they own, so investors may offer their shares to fund managers at an overvalued price. Lou (2012) finds that flow-induced trading has performance predictability in both fund performance and the stock returns of fund portfolios. He argues that flow-induced trading can explain performance persistence and the smart money effect since the inflow funds can add capital to their existing holding to drive up the stock price. Following the literature, I investigate the predictability of flow-induced trade for stock returns and fund performance in China.

Furthermore, the literature documents that fund managers do have active skills and a higher level of active management indicates better performance. Can active mutual fund managers exploit stock mispricing? Akbas, Armstrong, Sorescu and Subrahmanyam (2015) find that the aggregate fund flows of hedge funds show evidence to correct stock mispricing (Stambaugh, Yu and Yuan, 2012) by purchasing an undervalued stock and selling an overvalued one. In contrast, they find that aggregate trades of mutual funds are in the opposite direction, that buying an overvalued stock at an even higher price or selling an undervalued stock at an even lower price. Thus, aggregate hedge fund flows are labelled as smart money to correct stock return anomalies, while aggregate mutual fund flows are regarded as dumb money which exacerbates stock return anomalies. I examine the existence of anomaly returns in China and also study at the individual fund level to see if active fund managers have the ability to trade in stock return anomalies when experiencing money inflows or outflows.

In sum, motivated by the findings of the existing literature referred to above, I study three main questions that remain unexplored. First, a wide range of literature documents how factors such as risk-adjusted returns, risks and fund characteristics can drive fund flows. The priority and importance of these factors are largely unknown. If a sophisticated investor utilizes all these factors whether priced or unpriced, they should have different weights for these factors. To fill this literature gap, I employ Shapley-Owen R-squared decomposition and study the relative importance of risk and non-risk determinants.

Second, if managers understand the investment decisions of mutual fund investors, how can they manage cash holdings to accommodate fund outflows and inflows? To solve this problem, I comparatively study the determinants of cash holdings in the China and US markets. As abnormal cash holdings indicate active manager skills, the sources of the performance predictability or investment strategies of these funds remain unknown. I further study the investment strategies of these funds from the perspective of their risk exposures. Moreover, I examine how abnormal cash affects fund flows and fund performance.

Finally, as I have studied the flow mechanism from both investors' and fund managers' perspectives, does flow-induced trading create a profitable pattern to be exploited? I systematically examine the mechanism of flow-induced trading in China.[1] Also, studies show that on the aggregate level, sophisticated institutions can exploit stock return anomalies. However, limited studies explore whether mutual fund managers have the ability to exploit stock return anomalies on the individual fund level, rather than on the aggregate fund level. As active skills exist among mutual fund managers, do superior mutual fund managers trade on mispricing anomalies when experiencing capital flows? To fill these literature gaps, I interactively study the relation between flow-induced trade, active skills and the asset-pricing anomalies highlighted by Stambaugh, Yu and Yuan (2012).

The remainder of this chapter is organized as follows. In Section 1.2, I present the motivation, main findings and contributions of the three empirical chapters in this thesis. In Section 1.3, I show the structure of this thesis.

1.2 Motivation, Findings and Contributions

1.2.1 Relative Importance of Fund Flow Determinants

There is a large amount of literature studying flow determinants. However, less is known about which flow determinants are more important to investors. In the first place, investors should consider risk models to compare the cost of their capital. As for the studies on risk models, scholars find that CAPM outperforms all other risk

[1] Due to the availability of fund holdings data, I study the flow-induced trading pattern in China and compare to the US results studied by Lou (2012).

models in directing fund flows (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016; Agarwal, Ren and Green, 2018). In addition, scholars argue that a systematic investigation from both risk and non-risk perspectives of mutual fund flows might explain the fraction of flows that are unrelated to CAPM (Berk and Van Binsbergen, 2016). Investors respond more strongly to CAPM alpha rather than returns related to market beta. Also, sophisticated investors utilize more advanced benchmarks to evaluate fund performance (Barber, Huang and Odean, 2016). Moreover, hedge fund investors pool CAPM alphas with the returns associated with a range of non-market risks and attach more weight to exotic risk than traditional risk in their fund selection (Agarwal, Ren and Green, 2018).

Second, the literature documents that the active management skills of fund managers are predictors of superior fund performance. In active skill studies, funds with more concentrated investments in a few industries perform better (Kacperczyk, Sialm and Zheng, 2005). Fund managers with superior managerial skills rely less on public information in their investments. It has been found that funds with lower reliance on public information can outperform their peers with higher reliance on public information (Kacperczyk and Seru, 2007). The return gap between reported returns and returns calculated from a fund portfolio can measure unobserved actions of fund managers that add values. It positively predicts fund performance (Kacperczyk, Sialm and Zheng, 2008). Funds with greater diversification in response to size growth are associated with better performance (Pollet and Wilson, 2008). Funds with the highest active shares outperform their benchmarks and show strong performance persistence (Cremers and Petajisto, 2009).

Finally, investors can consider fundamental fund characteristics as they are widely accessible to investors and easy to calculate. Zheng (1999) finds that funds receiving higher money inflows subsequently outperform their peers that suffer redemptions. Chen et al. (2004) find that funds suffer from diminishing returns as size grows. Also, Sirri and Tufano (1998) find that funds with greater marketing efforts, a larger fund complex size and greater media attention can reduce the search cost of investors and enjoy higher money inflows. Moreover, Huang, Wei and Yan (2007) find that funds with greater marketing expense, star family affiliation and large family affiliation tend to have lower participation costs, which attracts money inflows. Consistent with Berk and Van Binsbergen (2016), non-risk factors are also of significance in driving mutual fund flows.

Motivated by the flow determinant literature, I seek to fill a literature gap and discover the relative importance of these measurements by applying a Shapley-Owen R-squared decomposition technique in flow-determinant regressions in both China and the US. The fast-developing China mutual fund market has a different background in terms of investor sophistication compared to the US, which enables me to further confirm the robustness of results.

I have the following key findings. First, I find that CAPM has the best performance in driving capital flows in the China market as well as the US market (Berk and Van Binsbergen, 2015). Second, from the perspective of decomposed R-squared, I find that non-risk factors outperform risk factors and risk-adjusted alphas in explaining fund flows in both markets. Specifically, it suggests that non-risk factors such as lagged fund flow, Morningstar ratings and fund size in the US, and lagged fund flow and fund size in China are the most crucial fund characteristics explaining fund flows. Third, I extend the investment horizon to a longer term (from one to three years). I find that fundamental fund characteristics show an increasing trend in its explanatory power to fund flows and non-risk factor group keeps outperforming risk factors and risk-adjusted alphas in the long term in China. Fourth, I examine if non-risk factors contribute to the success of CAPM in driving fund flows. In China, fund diversification and active shares have a positive impact on CAPM's success, while past volatility shows a negative impact on it. In the US, lagged flow shows a positive impact on it, but fund size negatively affects it. Finally, to examine whether decomposed R-squared can identify the smart money of sophisticated investors and predict fund performance, I propose a new proxy, Smart-to-Dumb Ratio (SDR). It measures if investors are performance-chasing or rationally consider fundamental fund characteristics in their fund selection. SDR significantly and positively predicts fund performance in the US. A high SDR also indicates superior skills on the fund family level, less reliance on public information from prime brokers, and the skills to exploit stock return anomalies. In sum, the findings provide evidence that non-risk factors are essential in the decision mechanisms of mutual fund investors.

My study first contributes to the growing literature on the determinants of fund flows. It sheds light on how fund flows can be explained by both risk effect and non-risk effect (Berk and Van Binsbergen, 2016). It is also relevant to the literature examining fundamental fund characteristics (Sirri and Tufano, 1998; Huang, Wei and Yan, 2007) and rating effect (Nanda, Wang and Zheng, 2004; Sharpe, 2008; Del Guercio and Tack, 2008). This unique and new anatomy systematically reveals the information criteria of mutual investors. I find that non-risk factors have substantial weight in their consideration.

Second, it provides new evidence on the relative importance of fund flow determinants (Barber, Huang and Odean, 2016; Agarwal, Green and Ren, 2018). As the literature develops, new determinants are identified. However, the importance of these new determinants can only be assessed in the context of existing literature. Important determinants in existing studies are often featured in regressions as control variables. The comparison of these determinants implies that the importance of a new determinant may be overemphasised. I highlight the importance of such a unified study and provide a framework for classifying the relative importance of flow determinants.

Third, I propose a novel measure, Smart-to-Dumb Ratio (SDR), to identify sophisticated investors and informative fund flows that predict superior fund performance. My work is associated with the literature on identifying well-performing funds (Kacpercyzk and Seru, 2007; Kacperczyk, Sialm and Zheng, 2005, 2008; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013) and the studies on smart money effects (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). Specifically, decomposed R-squared allows us to understand why an investor might purchase or withdraw their money based on fundamental fund characteristics, ratings, performance and risks. SDR has predictability for fund performance which may be widely utilized to identify funds with superior performance. I also provide robust evidence of an economically and statistically significant relationship between SDR and various risk-adjusted performance measures. Moreover, SDR extends our understanding of smart money effects since higher SDR funds outperform their peers. In other words, SDR may act as a threshold for smart money effects.

1.2.2 Cash Holdings and Liquidity Management

Fund managers, given their knowledge about the determinants of fund flow as studied in the first empirical analysis, should conduct proper cash management to maintain liquidity anticipating money inflows and outflows. Abnormal cash holdings have been found to be predictive of future fund performance. US funds with higher abnormal cash can outperform their peers with low abnormal cash by over 2% annually. Unobservable skill in stock selection and the ability to accommodate fund inflows or cover the cost of redemption are reflected in cash management (Smutin, 2014). Also, EU funds with higher abnormal cash holdings also outperform others by 0.48% over a six-month horizon. The cash holdings of EU funds are largely determined by their fund fee structure, lagged fund flows, flow volatility and funds' investment strategies (Graef et al., 2018). Further investigations of cash holding determinants between the China and US markets should reveal the decision mechanism of fund managers in liquidity management and enrich our knowledge of the consequences of smart money.

In addition, Boguth and Simutin (2018) find that average market beta can measure the tightness of constraints of mutual funds. Fund managers can tilt their portfolios to higher beta stocks as an implicit way to increase their leverage. But they find that funds with high risk-exposure generally underperform their peers with low risk-exposure by 5% annually. Also, Dong, Feng and Sadka (2017) document that funds with higher liquidity risk exposure are associated with better performance and outperform their peers with lower liquidity risk exposure by 4% annually. Extended analyses on the investment strategies on funds with high abnormal cash may enhance our understanding of the sources of abnormal cash. It allows us to know why funds which have additional cash outperform others.

Motivated by these studies and the different institutional backgrounds between China and the US, I endeavor to fill a literature gap: What mainly determines the cash holdings of mutual funds and how does abnormal cash affect mutual funds' future investment strategies? Especially, I compare the cash management of fund managers in China and the US to explore how risk and non-risk factors affect their cash holdings, how fund managers tilt their portfolio towards different risk factors, and I test the influence of abnormal cash on fund flows and future performance.

I find that, first, Chinese fund managers' decisions on cash holdings are more influenced by non-risk factors than risk factors to determine their cash holdings, while US managers are more affected by risk factors than non-risk factors. Especially, US managers are more concerned with the systematic risk factor. Second, fund managers with higher abnormal cash in the US are more inclined to reduce their risk exposure than are fund managers in China. The investment strategies of US funds holding abnormal cash are more conservative than those of funds in China. Third, abnormal cash can induce future money inflows in both China and the US. 1% increase of abnormal cash holding is significantly related to 0.162% (t=2.435) of fund inflows in China and 0.183% (t=2.959) of fund inflows in the US in the next quarter. Fourth, abnormal cash holdings have predictive power for future fund performance in the US market. A long-short strategy by sorting funds with the abnormal cash generates a monthly three-factor alpha of 0.065% (t=2.02) and a monthly four-factor alpha of 0.06% (t=1.85). Also, lagged flow appears to positively affect its predictability under the medium flow level in the US market.

This study first contributes to a wide range of studies on cash management (Yan, 2006; Simutin, 2013; Hanouna, Novak, Riley and Stahel, 2015; Graef et al., 2018). Also, it is related to studies on corporate cash holdings (Opler, Pinkowitz, Stulz and Williamson, 1999; Dittmar and Mahrt-Smith, 2007; Fresard, 2010). The results shed light on the differences in fund managers' decisions between developed and emerging markets. They show that in the developed market of the US, fund managers are more influenced by risk factors on their cash management, while in the emerging market China, fund managers are more affected by non-risk factors in determining cash holdings.

Second, it contributes to the strand of literature studying the risk-taking of fund managers in asset allocation (Frazzni and Petersen, 2014; Christoffersen and Simutin, 2017; Boguth and Simutin, 2018). The study provides empirical evidence to reveal sources of the performance predictability of abnormal cash holdings. It explicitly demonstrates that the trading practice of fund managers towards risk factors. The study also contributes to the papers examining investor preferences (Barber, Huang and Odean, 2016; Berk and Van Binsbergen, 2016; Agarwal, Green and Ren, 2018). Abnormal cash holdings also act as an essential signal for investors' fund decisions.

Third, this study contributes to the literature on fund performance predictions, including Simutin (2013), Cremers and Petajisto (2018), Kacperczyk, Sailm and Zheng (2006, 2007) and Chen et al. (2004), and smart money effects, including Gruber (1996), Zheng (1999), Wermers (2003) and Keswani and Stolin (2008). It provides investors with predictors of abnormal cash holdings (ACH) to identify well-performing fund managers.

1.2.3 Flow-Induced Trade, Active Management Skills and Stock Return Anomalies in China

Based on my studies of investor's decision mechanisms and fund managers' corresponding strategies in liquidity management, it is natural for a sophisticated investor to ask if a flow-induced trading pattern has performance implications. Coval and Stafford (2008) find that investors who trade against distressed mutual funds can earn significant positive returns by providing liquidity. Lou (2012) finds that flow-induced trade is positively associated with stock and fund performance. Anton and Polk (2014) also show that extreme flows to equity funds strengthen the comovement of the returns of their holdings.

As the China mutual fund market offered a relatively higher return (over 8% as shown in Chapter 3) in the last decade compared to the US market (a positive return close to zero), the study of flow-induced trading might offer a more profitable strategy and further confirm the robustness of the performance predictability of flow-induced trading. In addition, most of stock return anomalies are investigated in the US market, and limited studies focus on China. Motivated by both literature and industry characteristics, I examine the pattern of flow-induced trade with stocks anomalies in China.

In addition, a strand of literature documents that active management skill exists in mutual funds, which can be measured by an industry concentration index (Kacperczyk, Sialm and Zheng, 2005), return gaps (Kacperczyk, Sialm and Zheng, 2008), reliance on public information (Kacperczyk and Seru, 2007), fund diversification (Pollet and Wilson (2008) and active shares (Cremers and Petajisto, 2009). In contrast, the literature also finds that institutional investors can profit from mutual fund flows. It documents that hedge funds profit from front-running before mutual fund fire sales (Chen et al., 2008); the quarterly released data of mutual fund flows and mutual fund holdings contain information relating to fund performance, which is profitable to sophisticated investors, and such holdings are practical trading opportunities (Dyakov and Verbeek, 2013); hedge funds have capital to exploit mutual funds' holdings and trade on the predictions of mutual fund flows (Shive and Yun, 2013); mutual fund flows, on the aggregate level, tend to exacerbate stock mispricing (Akabas et al., 2015).

If active fund managers have skills, are they able to trade on stock return anomalies when experiencing money inflows or outflows? To understand how active management skills relate to flow-induced trade and stock return anomalies, I further examine if active fund managers, under price pressure from fund flows, have the ability to exploit the anomalies studied by Stambaugh, Yu and Yuan (2012). Different from Akbas et al. (2015), using aggregate fund flows, my study focuses on individual fund flows.

I have the following main findings. First, consistent with Lou (2012), I find that flow-induced trading (FIT) positively predicts stock returns in China. A long-short strategy based on the FIT has an annualized four-factor alpha of 4.2%. Flow-induced trading offers profitable opportunities for sophisticated investors. Second, the results show that anomaly returns based on Stambaugh, Yu and Yuan (2012) exist and active funds may have the ability to exploit these stock return anomalies in China. More specifically, skilled funds with higher return gap, higher industry concentration and higher diversification appear to trade on composite signals based on non-investment anomalies of return on assets, gross profitability, net stock issues, total accruals and momentum. Also, active funds appear to exploit the prior to 1997 anomalies of net stock issues, momentum and total accruals. Third, flow-induced trade is also predictive of fund performance in the short term. A long-short fund portfolio based on FIT generates an annualized four-factor alpha of 10.62%. Its predictability of fund performance might be partially explained by active fund skills. Fourth, using expected flows to construct FIT, I further confirm the robustness of the performance predictability of FIT.

The study first contributes to the literature studying the institutional price pressure (Coval and Stafford, 2007; Lou, 2012); it confirms the existence of patterns of flow-induced trade in China. The sophisticated investor may utilize flow-induced trade to earn positive returns by providing liquidity or flexibility to constrained mutual funds. It also implies that fund managers should consider the impact of their trade on their holdings and handle the influence of fund flows properly.

Second, it contributes to the literature on the skills of active fund managers (Berk and Green, 2004; Cremers and Petajisto, 2009; Kacpcyzk, Sialm and Zheng, 2006; Pollet and Wilson, 2008). It provides empirical evidence to support the existence of anomaly returns in China and examines if skilled active managers exploit stock return anomalies on the individual fund level, rather than on the aggregate level. The study presents empirical evidence that active fund managers may have the ability to exploit stock return anomalies. It indicates that the trades of active fund managers appear to be relatively smart and fund managers may consider a range of stock return anomalies.

Third, the study contributes to the literature on the smart money effect (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). It enriches our understanding of the consequence of smart money as fund managers vary in their investment philosophies based on active management skills. Fund performance predictions should be studied from the perspective of both sophisticated investors and skilled fund managers. It indicates that a two-dimensional perspective on smart money and active skills is essential to understand fund performance.

1.3 Structure of the Thesis

The remainder of the thesis is organized as follows. Chapter 2 reviews the literature on three empirical analyses, including mutual fund flows and their determinants, cash holdings and liquidity management, mutual fund flows and their performance implications. Chapter 3 describes the industry backgrounds of the China and US mutual fund markets. Chapter 4 examines the relative importance of risk and non-risk flow determinants. Chapter 5 studies abnormal cash holdings and their impact on mutual funds. Chapter 6 studies the performance implications of flow-induced trade and its relations to active skills and stock return anomalies. Chapter 7 concludes the thesis.

Chapter 2 Literature Review

This chapter reviews the relevant literature on funds. Section 2.1 summarizes the research on fund flows and their determinants, including risk-adjusted alphas, risk betas, fundamental fund characteristics, active investment factors and Morning ratings. It also reviews the literature on fund performance persistence. Section 2.2 examines the literature on cash holdings, fire sale costs, leverage constraints and risk-taking. Section 2.3 reviews the research on smart money and the performance implications of fund flows for both stocks and funds.

2.1 What Drives Mutual Fund Flows?

2.1.1 Determinants of Fund Flows

Earlier fund flow literature starts by exploring the flow-performance relationship. Researchers find that investors are sensitive to fund performance (Ippolito, 1992); fund managers receive incentives to take risks in flow-performance relationships (Chevalier and Ellison, 1997); fund inflows and outflows react asymmetrically to fund performance (Sirri and Tufano, 1998). Also, with a rational model approach to systemically explaining the active management of funds, Berk and Green (2004) document that fund flows react to performance rationally; they argue that even though fund performance is not persistent, differential ability and managerial talent still exist in the active management of mutual funds.

With the development of mutual fund studies, researchers have widely explored the determinants of fund flows. Notably, investors should utilize a risk model in their fund picking (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016); the active skills of fund managers indicate superior performance (Kacperczyk, Sialm and Zheng, 2005; Cremers and Petajisto, 2009); fund flows are sensitive to fundamental fund characteristics such as size, fees, and lagged flow (Sirri and Tufano, 1998; Chen et al., 2004; Huang, Wei and Yan, 2008). Consistent with these works providing mixed evidence that investors allocate their money to mutual fund based on specific criteria, I mainly review the studies on risk-adjusted alpha, risk beta, fundamental fund characteristics, active investment factors and Morningstar ratings in this section.

2.1.1.1 Risk-Adjusted Alpha

In recent literature, the risk measurement of mutual fund investors, especially their investment model, has been widely studied by researchers. Berk and van Binsbergen (2016) propose a new method that tests the outperformance of risk models with mutual fund flows. They find that CAPM is the closest model to the "true asset pricing model", which is inconsistent with the poor performance of CAPM in explaining cross-sectional returns. Similarly, Barber, Huang and Odean (2016) find that investors tend to use CAPM alpha rather than other risk-adjusted returns when assessing fund performance. CAPM best explains variations of fund flows. By running a model horserace with hedge fund flows, Agarwal, Green and Ren (2018) find that CAPM consistently outperforms other complicated risk models. In addition, hedge fund investors are CAPM alpha–driven, and they will not split the return based on other non-market risks such as size, value and momentum from the skill of fund managers (alpha).

All these studies show that investors are especially aware of market risk and adjust fund returns to obtain CAPM alpha. They might pool factor-related returns such as size or value premiums into risk-adjusted alpha. Interestingly, CAPM is documented as failing to explain cross-sectional stock returns (Fama and French

1992; Fama and French, 1993). However, it outperforms other risk models to fit fund flows. I call this confused evidence the "CAPM puzzle."

2.1.1.2 Risk Beta

The Literature also documents that investment behaviour of mutual funds is related to stock beta anomalies discovered by Frazzini and Pedersen (2014). Karceski (2002) finds that mutual fund investors chase well-performing funds over time and across funds, which causes fund managers to invest more in high beta stocks to outperform their peers. It reduces the premium of higher beta stocks, which distorts the conventional risk-return relationship. In addition, fund managers are important market participants who trade in betas. In line with this concept, Baker, Bradley and Wurgler (2011) suggest that investment managers do not exploit stocks with similar returns but high risks (volatility & beta) since this can only increase tracking errors of their performance. The anomaly whereby low-beta stocks, on average, outperform high-beta stocks is attributable to institutional investor's mandate to beat fixed benchmarks. Moreover, a stock itself is not isolated in the equity market. Huang, Lou and Polk (2016) show that when comomentum, measured by high-frequency abnormal return correlation among stocks (Lou and Polk, 2014), is relatively low, a strategy return trading on stock beta takes longer term (2-3 years) to be realized. When comomentum is high, abnormal returns occur within six months. They show that there is a positive feedback channel between arbitrage activity and beta anomalies. Beta-strategies of buying low-beta stocks and selling high-beta stocks can cause the cross-sectional spread in betas to increase. This beta expansion effect is even stronger when beta arbitrage activity is high and when beta arbitrageurs possess high leverage to trade. Furthermore, beta also provides investors with a way to detect the leverage of fund managers. Boguth and Simutin

(2018) find that mutual funds are constrained to take leverage on their investments, so higher beta stocks equate to implicit leverage for them. Empirically, a portfolio of higher beta assets will have relatively a lower alpha and Sharp-ratio.

These risk beta studies offer another perspective for investors to understand fund managers and fund performance. They let us know how much risk fund managers take to reward investors. The trade-off between risk-taking and performance should be included in the decision mechanism of sophisticated investors. Following these studies, I assume that investors will account for fund risk exposures since beta strategies are related to future fund performance. In my studies, I explore whether investors tend to consider risk beta from the CAPM , the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart model (Carhart, 1997), the Q-factor model (Hou, Xue and Zhang, 2014), the Fama-French five-factor model (Fama and French, 2015) and the mispricing-factor model (Stambaugh and Yuan, 2016).

2.1.1.3 Fundamental Fund Characteristics

2.1.1.3.1 Fund Size

Earlier literature has documented that fund returns show a decreasing trend as fund size grows, namely, scale-decreasing returns. Chen et al. (2004) find that fund returns significantly decrease with the growth of fund size. This effect is strong under different robustness tests. They further show that scale-decreasing return will be more pronounced in small-cap funds. To explain scale-decreasing returns, they argue that the interaction of fund liquidity and organizational diseconomies matters. When fund size grows, funds investing in small-cap stocks cannot find alternative investment opportunities. In addition, they might hire more managers to generate investment ideas. Consequently, if managers compete to implement their ideas, this will cause hierarchy costs. They find that solo-manged funds appear to outperform the co-managed fund with the control of fund size. This study points out that fund size is of crucial importance for investors to understand fund performance. To give more explanations on why fund size erodes fund performance, researchers also discuss it from a management perspective. Pollet and Wilson (2008) show that fund managers like to invest more money in their existing holdings and they are reluctant to find alternative investment ideas as fund size increases. In addition, the rate of diversification is slow to respond to size growth. Thus, diminishing returns to scale are caused by fund managers' inability to find investment ideas as their size grows. Moreover, Pástor, Stambaugh and Taylor (2015) point out that the growth of mutual fund industry size can reduce fund managers' ability to outperform passive indexes. The size should shrink to the level that matches the skill of managers. They state that the growth of the mutual fund industry can increase the competition between active funds, which impedes fund performance rather than improves skills. They also document that old funds tend to underperform because of industry size growth and the arrival of new and more skilled funds. In sum, these studies reveal that the scale-decreasing returns do have a link to active management skills.

Furthermore, Ferreira, Keswani, Miguel and Ramos (2013) find that international funds are not suffering from scale-decreasing returns. Their fund size does not negatively predict fund performance. This effect is due to the liquidity constraint faced by these funds. Because of their investment style, they are required to invest in domestic and small stocks. They show that scale-decreasing return is not universal for non-US funds. Funds invest overseas countries (non-US) with liquid stocks and strong legal institutions have better performance than funds that are constrained by their style, investing in the US in small stocks. They also find that solo-managed funds can outperform others because of their low hierarchy costs.

Moreover, Berk and Van Binsbergen (2015) find that managers' skills exist and should be measured by value, not gross or net alpha calculating from fund returns. They prove that manager skills measured by value and alpha have similar results only when the cross-sectional variation of fund size is smaller than that of fund fees. Also, the cross-sectional distribution of skills can only be explained by a small fraction of gross alpha. They suggest that a positive alpha indicates that a capital market is not competitive, while a negative alpha indicates that investors irrationally invest too much money in actively managed funds. The existence of large cross-sectional variation in funds size leaves no role for the gross alpha to measure fund skills. With insights into the hedge fund sector, Yin (2016) finds that hedge funds have incentives to collect more assets at the expense of fund performance. Also, fund managers restrict money inflows to maintain style-average performance.

In sum, fund size is associated with mutual fund studies on the "scale-decreasing returns." It raises an interesting debate as to whether fund managers can scale up their investment opportunities as their size grow larger. Also, fund size is easily accessible to investors in the fund prospectuses or monthly reports. Therefore, investors should be aware of size in their fund investments and understand its impact on fund performance.

2.1.1.3.2 Lagged Flows

Lagged fund flow initially relates to studies of the smart money effect which has been well documented in earlier literature. For lagged fund flow, Gruber (1996) finds that investors can identify superior fund managers. The strategy of following funds experiencing higher cash inflows can earn a subsequent positive risk-adjusted return so that the smart money effect exists. Zheng (1999) finds that funds receiving money inflows subsequently outperforms funds experiencing money outflows. The smart money effect is short-lived, and it is not explained by the momentum strategy of buying past winners. Also, the smart money effect is more pronounced in small funds. Opposite to the findings for smart money, Sapp and Tiwari (2004) argue that the evidence of the smart money is an artifact resulting from the stock momentum. They control for the momentum factor to examine fund portfolios with higher lagged flows. The results show that higher flow funds do not show much outperformance. With this finding, they state that investors do not have the ability to identify well-performing funds and they might simply chase past fund performance. By extending smart money studies to the UK mutual fund market, Kewani and Stolin (2008) carry on the debate about smart money. They find that the smart money effect exists in both the UK and US markets. With a unique dataset in investor profiles and monthly flow data, they find that the smart money effect is caused by the buying behaviour rather than the selling behaviour of both institutional and individual investors. They argue that the failure to find the smart money effect by Sapp and Tiwari (2004) can be attributed to their quarterly data frequency. Monthly data have more advantages to identify the smart money effect than quarterly data. It can also be attributed to the influence of the pre-1991 period.

In addition to smart money studies, fund flows are also related to studies on institutional price pressure. Coval and Stafford (2007) find that fund flows are sticky on both quarterly and monthly level. This is strongly related to past fund returns and lagged fund flows. They regress fund flow on lagged fund flows and fund returns from the previous eight quarters with the Fama-MacBeth (1973) and pooled OLS regression. The results indicate that lagged fund flows and returns have good explanatory power (R-squared) ranging from 35.89% to 53.45%. Moreover, with a focus on the impact of fund flows on fund managers' trades, Lou (2012) finds that lagged flow significantly affects the trading behaviour of fund managers. Trades motived by lagged flows have a positive impact on both stock returns and fund performance. A past winning fund can attract more inflows and invest more in its existing holdings which drives up the stock price, while a previous loser fund suffers from money outflows and liquidates its holdings which drags down the stock price. He argues that this flow-induced pattern fully explains mutual fund performance persistence. Further investigations have examined the relationship between hedge fund flows and mutual fund flows, Shive and Yun (2012) find that hedge funds can profit from predictable flow-induced trade by mutual funds. The larger disclosure of mutual fund portfolio and more patient capital can enhance this effect. The premium is even stronger for more constrained mutual funds. Investors should consider lagged fund flow as one criterion affecting future fund performance.

To sum up, the mutual fund literature has widely discussed whether investors have the ability to pick superior performing funds or if money is smart, known as the "smart money effect." In addition, money inflows and outflows are influential on the behaviour of fund managers, and they also imply the ability of fund managers to handle their portfolio liquidity. Moreover, the consequence of the smart money flows for well-performing or under-performing funds may also be attractive to explore. So, investors should include fund flows in their investment decision-making.

2.1.1.3.3 Fund Fees

As for fund fees, Sirri and Tufano (1998) find that fund flows are fee-sensitive and investors respond disproportionately to well-performing and under-performing funds. They find that high-fee funds that spend more marketing efforts than their peers can reduce the search cost and attract more money inflows. By studying which fees matter to investors, Barber, Odean and Zheng (2005) find that fund flows show a negative relation to the front-end load but no relation to operating expenses. However, they document that investors are sensitive to marketing expenses (12b-1 fees) as part of operating expenses. It shows that in-your-sight fees affect investors' fund decisions significantly and the marketing of mutual funds does work to attract money inflows. Mutual fund investors choose funds with lower front-end loads and higher marketing expenses. The positive effect of marketing expense does not appear to be sufficient to offset the negative effect of other expenses.

Moreover, Huang, Wei and Yan (2007) find that participation costs measured by marketing expenses and other fund characteristics affect the sensitivity of fund flows to fund performance. They argue that investors with different levels of financial sophistication have threshold values to realize their utility gains in investing mutual funds. If funds have better performance exceeding these threshold values, they can attract investors to overcome costs in investigations and investments. Hence, investors are increasingly more sensitive to better past performance. They find that investors with different levels of participation costs have different sensitivities to past performance. At a medium performance level, funds with higher marketing expense, the affiliation of star fund families, larger fund family size and a larger number of fund categories can reduce participation costs and attract more money inflows. In addition, Gil-Bazo and Ruiz-verdu (2009) find that funds' before-fee performance is negatively associated with fund fees. More specifically, first, investors in underperformed funds show less sensitivity to sell their shares, so these funds optimally increase their fees (Christoffersen and Musto, 2002). Second, underperforming funds target performance-insensitive investors to set higher fees, while well-performing funds set lower fees since more sophisticated investors would choose them and these investors are more performance-sensitive

(Gil-Bazo and Ruiz-Verdu, 2009). Third, funds that are expected to underperform will be marketed to performance-insensitive investors and charge higher distribution costs which turn into fund fees. As fund fees directly affect how much return investor can receive from fund investments, I include it as one criterion in fund decision analysis.

2.1.1.3.4 Other Fund Characteristics

There is also a small body of literature showing that fund characteristics, including fund family size, fund age, manager tenure, fund volatility and fund turnover can affect the investment decisions of mutual fund investors.

For fund family size, Sirri and Tufano (1998) find that funds in a large family receive more substantial money inflows than their peers. They also find that flow-performance sensitivity tends to be stronger in a large fund family. Huang, Wei and Yan (2007) find that fund flows increase their sensitivity to fund returns in larger a fund family or a fund family offering more diverse fund categories. Bhojraj, Cho and Yehuda (2011) find that fund family size can positively predict fund performance before regulatory changes, while its predictive power decrease in the subsequent period of regulatory changes. Regulatory changes include regulation fair disclosure, global settlement and increased scrutiny. Nanda, Wang and Zheng (2004) find that higher variation across fund returns within a fund family can produce more star funds. A star fund has a spillover effect in that it attracts flows for other funds within a fund family.

For fund age and manager tenure, Bai et al. (2018) find that relatively old funds outperform their young peers by 0.48% annually. They argue that increased confidence explains the skills of old funds managers. Old fund managers show more confident behaviour that they make larger bets, conduct less window-dressing adjustments in their portfolios and utilize better product marketing. A longer manager tenure indicates better fund performance. Moreover, Pástor, Stambaugh and Taylor (2015) find that young funds tend to outperform old funds since the active skills of mutual fund industry increase over time. Continuing growth in industry size and the arrival of new skilled managers enhance industry competition and reduce the performance of old funds. Fortin et al. (1999) find that manager tenure positively predicts fund size, but it is negatively associated with fund turnover. They argue that investors who are looking for low turnover funds should consider funds with long manager tenure. For fund volatility, Huang, Wei and Yan (2004) find that a sophisticated investor consistently responds to past fund performance via measurement of rational models. The sensitivity of flows to returns decreases in funds with higher volatility and longer tracking records, and it varies between naive investors and sophisticated investors. For fund turnover, Cremers and Pareek (2016) find that the performance predictability of a fund's active share is affected by how frequently fund managers trade. Funds with high active shares that trade infrequently tend to outperform. But, funds that trade infrequently and have low active share tend to underperform.

2.1.1.4 Active Investment Factors

Existing literature also supports the value of active fund management. Recent studies provide empirical evidence for the existence of active management skills. Empirically, Gruber (1996) find that the active management industry, on average, offers a negative risk-adjusted return to investors, but investors still invest their money in it. He explains that net asset value cannot reflect active management skills. If active management skill exists, sophisticated investors can take advantage of these to select funds. He finds evidence that risk-adjusted return earned on new money flows is positive which indicates that smart investors who recognize superior management skills exist.

In addition, focusing on industry sectors of investments, Kacperczyk, Sialm and Zheng (2005) find that industry concentration index can represent the investment ability of fund managers. Funds that invest in concentrated industries have better performance than diversified funds controlling for risk and style. Concentrated Funds have a distinct investment style and put more holdings on growth and small funds, while diversified funds are likely to replicate the total market portfolio. Skilled fund managers have more knowledge and experience in a few industries. With a focus on analyst recommendations, Kacperczyk and Seru (2007) find that a skilled manager has more private information about their investments, and the reliance on public information (RPI) is low for their asset allocation. The RPI can be applied to identify whether performance is attributable to analyst recommendations or advantageous information held by fund managers. Investigating into fund portfolios, Pollet and Wilson (2008) find that funds with more diversified holdings, measured by the number of stocks in their portfolios, have better future performance than their peers with lower diversification. They show that fund managers are not able to scale up their investment ideas due to liquidity constraints which also explains the diminishing returns on fund size.

Moreover, Cremers and Petajisto (2009) propose "active share" to measure the investment activeness of fund managers. They define the active share as the difference between the weight of a fund portfolio and the weight in its benchmark portfolio. They find that funds with higher active share have better performance and exhibits strong performance persistence. Jain and Wu (2000) find that advertising drives money inflows. Funds advertised in Barron's and Money magazine show significant positive capital flows, which are about 20% higher than unadvertised funds. They document that advertising is one way to reduce the search cost (Sirri and Tufano, 1998) of the mutual fund investor in fund selection. Utilizing more accessible data rather than fund holding data, Amihud and Goyenko (2013) find that R-squared, obtained from regressing fund returns on market, size, value and momentum factor, is a predictor of fund performance. They document that funds with a lower R-squared have greater selectivity and activeness. They suggest that the R-squared is more easily obtained than the measures computed using the mutual fund holding data (Kacpercyzk, Sialm and Zheng, 2005; Cremers and Petajisto, 2009); they also find that R-squared is positively related to funding size, but negatively related to fund fees and manager's tenure.

2.1.1.5 Morningstar Ratings

For Morningstar ratings, Blake and Morey (2000) find that a low Morningstar rating can predict poor future performance, but a five-star Morningstar rating shows weak significance to perform better than four-star and three-star funds. They find that Morningstar rating is slightly better than returns, Sharpe ratio, CAPM alpha and four-index alpha (Elton, Gruber and Blake, 1996) in predicting the future fund performance. In an event study on Morningstar ratings and fund flows, Guercio and Tkac (2008) find that Morningstar ratings can drive fund flows. Investors are sensitive to changes in star ratings rather than changes to fund performance of their fund allocations. Investors punish funds when they drop to 3-star ratings (or below the one-third of rated funds) and they respond disproportionately and positively when ratings rise to 5 stars. By investigating newly launched Morningstar analyst ratings, Armstrong, Genc and Verbeek (2017) find that funds with higher Morningstar analyst ratings receive higher money inflows. Different from traditional

Morningstar ratings, which are based on risk-adjusted fund performance, qualitative and forward-looking Morningstar analyst ratings, which judge funds on their people, parent, process, performance and price, significantly predict fund performance. Gold-rated funds outperform not-recommended funds by about 120 basis points annually. The simple strategy of investing equally in gold-rated funds can earn a positive return. Extending the analysis to fund family level, Nanda, Wang and Zheng (2004) find that the Morningstar rating induces a spillover effect in fund flows. A star-rated fund can attract alternative money flows to funds within the same fund family. They suggest that simply chasing a star fund in a fund family does not generate a positive return for investors. In addition, fund families with lower variation in investment strategies to produce stars tend to perform better than their peers.

2.1.2 Performance Persistence

The literature widely explores if performance persistence exists and how long does it last. A strand of literature shows that performance persistence exists. Grinblatt and Titman (1992) find that performance persistence exists over time and is attributable to the superior investment skills of fund managers. Hendricks, Patel and Zeckhauser (1993) find that the relative performance persistence of growth-oriented and no-load funds exists for one year. Long-short fund portfolios constructed based on past performance generate an annual risk-adjusted return of 6% to 8%. They use post-1988 data to confirm the performance persistence. Carhart (1997) finds that the one-year momentum of Jegadeesh and Titman(1993) mostly drives the performance persistence found by Hendricks, Patel and Zeckhauser (1993). They also argue that performance persistence is short-lived. They claim that the skill of fund managers does not exist since the future alphas of past winning funds are not significant in robustness checks. This is consistent with top performing funds only earning back their investment costs with a higher total return.

Another strand of literature states that performance persistence varies across time and is short-lived. Brown and Goetzmann (1995) find that the performance persistence of US funds depends strongly on the period studied. They find that relative performance persistence does exist. A benchmark such as the SP500 index can be used to calculate the relative performance. Bollen and Busse (2005) find that mutual fund performance is not persistent in the long term and the impact of superior management skills is short-lived. Berk and Green (2004) show that fund performance is not persistent in their model. Investors competitively supply money to fund managers, but fund managers have decreasing returns in employing their ability. They increase their fund size and compensations to the point that investors' expected return going forward is competitive. So, funds' performance can be finally eroded by fund size as they grow larger (Chen et al., 2004).

In sum, the literature shows that persistence performance is often short-lived and varies across time. More explicitly, buying funds that have superior past performance does not generally reward investors with higher premiums in the future. However, short-lived persistence in fund performance may attract investors to allocate their money in mutual funds. Naive investors might simply chase past performance, while sophisticated investors should recognize performance persistence as an important consideration in their decision-making.

2.1.3 Summary of Literature Gaps

CAPM outperforms other risk models in driving mutual fund flows (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016). Berk and Van Binsbergen (2016) argue that expected fund return may be a function of risk and non-risk factors. However, they provide less empirical evidence to support the existence of non-risk effects. Barber, Huang and Odean (2016) also argue that sophisticated investors may utilize all factors that are priced or unpriced in their fund selection. It remains unclear how investors weigh risk and non-risk factors in their fund selection. I intend to fill these literature gaps and examine the existence of non-risk effects and the relative importance of risk and non-risk based flow determinants.

2.2 Cash Holdings and Liquidity Management

2.2.1 Cash Holdings of Mutual Funds

Regarding cash holdings, scholars emphasize that there is a tradeoff between the cost of holding cash and the flexibility of holding cash to meet fund redemptions. Yan (2006) develops a model and finds that there is a trade-off between the benefits of holding cash and liquidating existing stocks to meet fund redemptions. They suggest that funds with small-cap holdings, more volatile lagged flows and large recent inflows tend to hold more cash. Also, they find funds with greater money inflows tend to hold more cash since they trade infrequently. In contrast, they find that funds with lower cash holdings do not show superior stock picking ability. Aggregate cash holdings positively predict future fund flows. However, aggregate cash holdings cannot predict fund performance, which indicates that on average equity funds lack market timing skill. In addition, by jointly considering fund cash holdings and fund fees, Chordia (1996) finds that mutual funds carry more money when they are uncertain about fund redemptions, while funds with high redemption costs such as loads and redemption fees tend to hold more cash. They also find that aggressive growth funds are more sensitive to fund flows and rely more on load fees rather than cash to reduce redemptions since they hold smaller and more illiquid stocks.

Moreover, several theoretical and empirical papers study the relation between cash holdings and fund performance. In line with the idea that holding cash is costly, Wermers (2000) finds that equity funds, on average, outperform the market by 1.3% in total return, but in net returns, they underperform the market by 1% from 1975 to 1994. About this 2.3% difference, non-stock holdings explain 0.7% of the erosion of fund performance, while the rest of the 1.6% of underperformance is attributed to fund expenses and transaction costs. He documents that cash holdings, which presumably are held to meet redemptions, substantially reduce net fund returns. However, this study should have considered the benefits of cash holdings to accommodate fund flows.

In contrast, scholars fund that fund managers can benefit from holding additional cash. Simutin (2013) finds that abnormal cash holdings have predictive power in relation to future fund performance. Abnormal cash is significantly determined by expense ratio, fund size, fund returns, fund flows, market beta, portfolio holding characteristics and fund age. To extend the analysis to the European market, Graef et al. (2018) find that both EU and US funds with higher abnormal cash holdings tend to outperform their peers with lower abnormal cash. They document that cash holdings are determined by funds' fee structure, past flows, flow volatility and investment strategies. Furthermore, from the perspective of liquidity transformation, Chernenko and Sunderam (2016) find that funds tend to hold substantial cash to accommodate fund flows rather than liquidate their existing holdings. They suggest that this liquidity transformation depends on the liquidity provision by banks and the shadow bank sector. Funds have to carry additional cash and bank deposits to provide liquidity to investors. While the cash holdings they have are not large enough cannot mitigate the price impact from providing investors with liquidity.

2.2.2 Fire Sale Costs

When funds experience massive money outflows, they might transact their existing holdings at disadvantageous prices. To reduce the possibility of an assets fire sale, fund managers would hold a certain amount of cash to maintain fund liquidity. Edelen (1999) finds that the underperformance of open-end mutual funds is due to the costs of liquidity-motivated trading. Controlling for the cost of providing liquidity to investors, the average abnormal return of equity funds changes from significant -1.6% to insignificant -0.2% per year. They argue that the average underperformance of mutual fund does not indicate a lack of ability of fund managers; it is a consequence of the liquidity service provided by fund managers to investors. The market timing ability of fund managers become significant and positive if controlling for flow-related liquidity trades.

As liquidity-motivated trading affects fund performance, how do investors react to it? By studying flow-motivated trade and fund liquidity provision, Coval and Stafford (2007) find that flow-driven trade in constrained funds is predictable and investors can profit from trading against to provide liquidity. Funds facing massive money outflows will transact their existing positions, which induces price pressure on securities mutually held by other funds. While funds facing large capital inflows have a positive price impact on their overlap holdings. In addition, Lou (2012) finds that flow-induced trading can explain the performance persistence of mutual funds and the smart money effect, and partially explains the stock price momentum. He argues that past winners can attract money inflow and invest in their existing holdings, while past losers are forced to liquidate their holdings to satisfy redemptions. This generates a pattern that drives stock prices of past winner funds so that they consistently outperform losers, which explains the performance persistence. It also explains the smart money effect that funds with higher lagged flows tend to outperform their peers with lower lagged flows.

2.2.3 Leverage Constraints and Risk-Taking

With a focus on portfolio management, a small but growing strand of literature studies risk (beta) strategies and the leverage constraints of mutual funds. Boguth and Simutin (2018) find that the average market beta of their portfolios can capture the desire to exert leverage and the tightness of the leverage constraint of fund managers. Fund managers may choose to increase their portfolio beta rather than directly use leverage due to their investment constraints. Consistent with the betting-against-beta study by Frazzini and Pedersen (2014), low-risk exposure funds outperform high-risk exposure funds by 5% per year. In addition, with a focus on pension investments, Christoffersen and Simutin (2017) find that fund managers with largely defined contribution assets have an incentive to tilt their portfolios to high-beta stocks since defined-contribution (DC) plan sponsors monitor their performance relative to benchmarks which can exacerbate stock return anomalies. DC plan sponsors do not penalize fund managers for selecting high-beta stocks with low or negative alphas since DC fund flows are determined by relative returns rather than alpha or beta. Moreover, Andonov, Bauer and Cremers (2017) find that US pension funds take advantage of regulatory guidelines to strategically maintain higher liability discount rates by increasing risky asset in their portfolios. Funds with a higher level of underfunding per holder and funds with more politicians and elected plan holders, take more risks and employ higher discount rates. This increase in risk-taking behaviour is negatively associated with pension fund performance.

2.2.4 Summary of Literature Gaps

Simutin (2013) finds that abnormal cash holdings predict better fund performance. However, less literature studies how fund managers weigh different factors to determine their cash. In addition, Simutin (2013) explains that fund managers who hold abnormal cash can benefit from purchasing stocks quickly when new investment opportunities arise. Existing literature shows limited understanding of the relative importance of cash determinants. Also, limited studies in cash management explore which risk factors fund managers would prefer to purchase. I fill the literature gap by applying Shapley-Owen R-squared decomposition to study the relative importance of cash determinants. Also, I intend to fill the literature gap on the future investment strategies of mutual fund managers with high abnormal cash. Moreover, I seek to understand how abnormal cash holdings affect fund flows and fund performance in the China and US markets.

2.3 Mutual Fund Flows and Performance Implications

2.3.1 Smart Money vs Dumb Money

Money flows to mutual funds have been labeled by scholars as "smart money" and "dumb money" under different rationales. On the one hand, mutual fund managers might buy too much of what they own under inflows or liquidate their holdings at disadvantageous prices under outflows. On the other hand, some mutual fund managers possess skills in active management and add value for investors.

The literature documents that sophisticated investors can trade on the price pressure and liquidity constraints of mutual funds. Chen et al. (2008) examine if hedge funds engage in front-running trading when mutual funds suffer massive outflows. They find that hedge funds can take advantage of fire sales of mutual funds. They empirically demonstrate that long-short equity hedge funds profit greatly when the mutual fund sector is in distress. In addition, they document that the short interest of stock rises more substantially before the fire sale of mutual funds, which supports the front-running mechanism of hedge funds. With further empirical investigations, Dyakov and Verbeek (2013) find that a front-run trading strategy targeting fire-sale mutual funds generates a monthly alpha of 0.5% from 1990-2010. Specifically, the premium is from small stock below the average size of stock on the NYSE. The premium is robust, and new public information cannot explain it. It provides evidence that publicly available mutual fund holdings and fund flows are profitable sources for sophisticated traders. Moreover, Arif, Ben-Rephael and Lee (2015) find that mutual funds and the short sellers trade in opposite directions. When a mutual fund increases its net purchase, a short seller engages in more short-selling activities. Both expected mutual fund flow based on the prior day's trade and unexpected mutual fund flows based on the current day are related to the negative relation between mutual funds' trading and the selling of short-sellers. Short sellers profit from mutual funds, and this is more pronounced for stocks highly held by mutual funds, for stocks with low liquidity, and for periods with higher retail sentiment measured by the flows from bond funds to equity funds (Ben-Rephael, Kandel and Wohl, 2012).

Furthermore, scholars have comparably studied mutual fund flows and hedge fund flows. They show that hedge fund managers appear to regard mutual fund flows as an important signal to trade. Shive and Yun (2013) find that flow-induced trading by mutual funds is a profitable pattern for hedge funds to exploit. They empirically show that a 1% volume change in mutual funds' trade in stock motived by fund flows in the forthcoming quarter is associated with 0.29% to 0.45% of hedge fund trades in the current quarter. This effect is stronger when hedge funds have more patient capital and when mutual funds are required to disclose their quarterly holdings. Empirically, a standard deviation increase in hedge fund trading sensitivity to mutual fund flows is associated with a 0.9% increase in four-factor alpha per annum. A standard deviation increases in expected mutual funds' trade is associated with a 0.07% to 0.15% decrease in four-factor alpha per annum. This profitable trading mechanism is more pronounced for more distressed mutual funds.

In addition, Barber, Huang and Odean (2016) argue that hedge fund flows are also an important metric to test investor preferences in asset pricing models. Hedge fund managers can purchase an undervalued mutual fund and sell an overvalued one. Meanwhile, a similar strategy of following an undervalued mutual fund can be conducted by a hedge fund. Thus, hedge fund flows also provide information about the "true asset pricing model" studied by Berk and Van Binsbegen (2016). Nevertheless, less literature addresses smart money within mutual funds. From the perspective of stock return anomalies, Akbas et al. (2015) find that aggregate mutual fund flows tend to exacerbate the anomalies investigated by Stambaugh, Yu and Yuan (2012). They trade in the reverse direction and tend to buy overvalued stocks and sell undervalued stocks. This effect is stronger for asset growth, total accruals and momentum anomalies. However, aggregate hedge fund flows show evidence of exploiting stock return anomalies. Therefore, they label mutual fund flows as dumb money but hedge fund flows as smart money.

In contrast, recent literature documents that the active skills of fund managers do exist. Cremers and Petajisto (2009) propose a proxy, Active Share, which is based on mutual fund holdings. They utilize the difference between the weight of the stock in a fund portfolio and the weight of the stock in a portfolio of the fund's benchmark to construct it. This measure allows investors to assess the active management skill of fund managers in stock selection, factor investing and indexing. Funds with higher active shares outperform peer funds with lower active shares, and they also demonstrate strong performance persistence. In addition, they find that a significant amount of large funds are index followers with relatively lower active share, while small funds are more actively investing stocks deviating from their benchmarks.

Moreover, Kacperczyk, Sialm and Zheng (2005) find that superior fund managers have investment skills and advantageous information in specific industries, and they invest in a more concentrated way in a few industries. Especially, they tilt their portfolios to growth and small stocks in a few sectors, and this exhibits a distinct investment style. In contrast, the allocations of well-diversified fund managers are close to the market portfolio. They propose an industry concentration index to measure the skill of fund managers. They find that funds with higher industry concentration perform better than their peers, even controlling for various risks. Kacperczyk and Seru (2007) find that skilled fund managers possess private information about their investments, and their allocation in portfolios rely less on publicly available analysts' recommendations. They propose a proxy, reliance on public information, which utilizes the R-squared by regressing the changes in fund holding of stocks on the prior analyst recommendation scores of these stocks. R-squared indicates, to what extent, fund managers' trading is driven by public information. Funds with lower reliance on public information exhibit better performance and attract more money inflows. Pollet and Wilson (2008) find that fund managers are not able to enlarge their investment opportunities as their size grows. This explains the diminishing return on scale. They also find that the diversification is associated with fund skill. Funds with greater diversification can outperform their peers with less diversification. This effect is more pronounced for small funds. They also find that, for the size growth of a fund family, they prefer to launch new funds with different investment ideas rather than add capital to their existing funds.

2.3.2 Mutual Fund Flows and Stock Returns

Earlier literature identifies a positive relation between aggregate fund flows and market returns. Warther (1995) finds that the aggregate mutual fund flows positively affect stock market prices. The security price index increases by 5.7% if the mutual fund market experiences an unexpected inflow of 1%. The increase in security price is more significant for stocks held by mutual funds. But this study does not present adequate explanations for such a positive relation between fund flows and stock price. Utilizing daily fund flow data, Edelen and Warner (2001) also document that the relation between aggregate mutual fund flows and stock market returns is positive. They suggest that institutional trade does affect market returns. Also, they find that there is a strong relationship between the previous day's return and fund flows indicating a performance-chasing phenomenon, but there is a one-night gap in such a relation. However, the study cannot adequately distinguish performance-chasing investors from other explanation of overnight trading.

To further study the price pressure on mutual funds of stocks when experiencing extreme money flow, Coval and Stafford (2007) find that mutual funds tend to transact their shares at a price under their fundamental value. Investors can trade on the constraints of mutual funds to earn significant returns for providing liquidity.[2] Additionally, Frazzini and Lamont (2008) find that fund flow is dumb and stocks owned by mutual funds with massive counterfactual inflows will subsequently have lower returns. With substantial fund flows, firms issue overvalued stocks to investors and repurchase them when they are undervalued. More specifically, in the return predictability of mutual fund flows, Ben-Rephael, Kandel and Wohl (2012) find that one standard deviation of the aggregate net flow between bond funds and equity funds in a fund family can result in 1.95% of market excess return.

Further studies require a proxy for the price pressure of institutional investor. Lou (2012) proposes flow-induced trading and examines its performance implications for stocks and funds. He finds that the persistence of mutual fund performance is adequately explained by flow-induced trading. Investors can utilize a flow-induced trading mechanism to achieve significant premiums from both stock and fund levels. The return pattern based on flow-induced trade does not suffer from a large reverse in the first year after formation; it takes two years to diminish. From the perspective of arbitrage theory, Akbas, Armstrong, Sorescu and Subrahmanyam (2016) find that substantial money flows from an arbitrage fund that trades on cross-sectional inefficiencies will lower the future return of market anomalies and improve market efficiency, and vice versa. Moreover, Akbas et al. (2015) find that aggregate mutual fund flows have adverse allocation effects and exacerbate stock mispricing, while hedge fund flows contribute to the correction of cross-sectional mispricing. However, they have not studied mutual funds' trades in stock return anomalies at the individual fund level, especially for skilled funds

[2] Also, Shive and Yu (2016) find that hedge funds trade on the predictions of mutual fund flows, especially for more constrained mutual funds. Hedge funds can profit from mutual funds' flow-induced trade.

identified by active investment measures (Kacperczyk, Sialm and Zheng, 2005; Kacperczyk and Seru, 2007; Cremers and Petajisto, 2009).

In conclusion, the literature shows evidence that the persistent money flows of mutual funds can drive up the price of their existing holdings, which creates a profitable pattern for institutional or retail investors. Also, by providing liquidity for distressed mutual funds, investors can earn significant positive returns.

2.3.3 Mutual Fund Flow and Fund Performance

From the perspective of trading on lagged fund flows, scholars construct fund portfolios sorted by past fund flows (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008; Yu, 2012). Also, they regress portfolio excess returns on risk factors, such as size, value and momentum factor to obtain risk-adjusted alphas. They find that funds with higher flows tend to have higher risk-adjusted alphas than funds with lower flows. This indicates that lagged fund flow is predictive of future fund performance and the smart money effect exists.

More specifically, to solve the puzzle that investor prefers to buy mutual funds with average inferior performance compared to passive funds, Gruber (1996) initiates the "smart money" effect, and he studies if investors have the ability to pick well-performing funds. He claims that, even if the average risk-adjusted return of the mutual fund industry is negative, superior management skills do exist. This is not reflected in net asset value (NAV). He argues that sophisticated investors can identify it and benefit from supplying new cash flows. Furthermore, Zheng (1999) also examines the existence of the smart money effect with a large fund dataset. She finds that the smart money effect is short-lived and not attributable to a momentum strategy. She further addresses that the smart money effect is more pronounced in small funds. However, Sapp and Tiwari (2004) deny the smart effect; they argue that investors are naively performance-chasing in their fund selection. They find that the smart money effect does not exist after controlling for the momentum factor.

In contrast to Sapp and Tiwari (2004), Keswani and Stolin (2008) find that the smart money effect robustly exists in the UK even after controlling for momentum factors, and it is caused by the money inflows (buying), not outflows (selling), of both individual and institutional investors. They reexamine US evidence and find the smart money effect exists in the US after 1991 as well. They argue that Sapp and Tiwari (2004) should consider monthly, rather than quarterly flow, and consider the influence pre-1991 to detect the smart money effect. Further confirmation of the smart money effect demonstrated by Yu (2012), he finds that top-performing small funds with new money inflows subsequently outperform others in the US, which is mainly attributable to the market-timing ability of investors. The result is robust even after controlling for the momentum factor. Moreover, Goldstein, Jiang and Ng (2017) find that the flow-performance relationship is asymmetric in corporate bond funds. Investors show more sensitivity to poor performance in outflows than sensitivity to inflows based on superior fund performance. This asymmetric relationship is even stronger when they have fewer cash holdings or more illiquid assets, and when overall market illiquidity is high.

2.3.4 Summary of Literature Gaps

Lou (2012) finds that flow-induced trading positively predicts stock returns held by fund managers. The predictability of flow-induced trading in an emerging market, China, is unknown. In addition, Akbas et al. (2015) find that, on the aggregate level, hedge flows tend to correct mispricing anomalies while mutual fund flows tend to exacerbate them. Existing literature has limited investigations on the flow-induced trade in China and it remains unclear whether active mutual funds are able to explore stock return anomalies on the individual fund level. I fill these literature gaps and study whether the pattern of flow-induced trading exists and if active fund managers are able to explore stock return anomalies when they experience money inflows and outflows in China.

Chapter 3 Mutual Fund Industry Characteristics of China and the US

This chapter reports the industry characteristic of the China and US mutual fund market. Sections 3.1.1 and 3.2.1 review the development of the mutual fund market. Sections 3.1.2 and 3.2.2 describe aggregate fund size, fund performance, and fund flows by each fund category. Sections 3.1.3 and 3.2.3 show the mutual fund investor profiles of the China and US mutual fund markets respectively. Section 3.3 concludes this chapter.

3.1 China Mutual Fund Industry

3.1.1 Brief History of the China Mutual Fund Market

The historical development of Chinese mutual funds can be defined in three periods, the earlier development period, the closed-end fund development period and the open-end fund development period (China Security Regulatory Commission, 2007).

The first stage is defined as the period from 1992 to the launch of the ***Interim Measures for the Management of Securities Investment Funds*** on 14 November 1997, which is known as the earlier development period. The Shanghai stock exchange and the Shenzhen stock exchange launched, respectively, in December 1990 and July 1991, which provided the foundation for securities transactions. On 4 October 1991, the first investment fund, "Wuhan Security investment fund", was issued by the People's Bank of China with a capitalization of 10 million yuan (Wu, 2006). In November 1992, the first closed-end mutual fund "Zibo Town Enterprise Investment Fund" was issued by the Chinese agriculture development investment trust and the Bozi investment trust, raising a capitalization of 300 million yuan with an 8-year lock-in period. The launch of "Zibo" fund prompted a wave of fund investments in China as well as a series of issues in the operation and regulation of the new funds.

The second stage is the period from the launch of the ***Interim Measures for the Management of Securities Investment Funds*** to August 2001, which is the period of closed-end mutual funds. On 14 November 1997, to protect the legitimate rights and interests of mutual fund investors and promote sustainable development of the mutual fund market, the *Interim Measures for the Management of Securities Investment Funds* was released by the Securities Regulatory Commission of the State Council, which provided the legal foundation for mutual fund investments. Funds are required to have at least 10 million (yuan) registered capital with qualified personnel handling fund management and specific investment plans, have a record of 3 years continuous profit, and the paid-up capital of each sponsor must be no less than 300 million yuan. It also specifies that the launch of a mutual fund must only be approved by the China Securities Regulatory Commission, not regional government, which marks a primary phase of mutual fund development in China (Security Association of China, 2006). On 27 March 1998, the closed-end funds "Kaiyuan" and "Jingtai" were launched, with an average capitalization of two billion yuan. The mutual fund industry proliferated quickly with the support of policies. By September 2001, the number of closed-end funds increased to 47, and the aggregate capitalization rose to 62.054 billion yuan.

The third stage is from September 2001 to now, the period of open-end mutual funds. On 8 October 2000, the China Securities Regulatory Commission released ***Trial Measures for Open-end Mutual Funds*** to further regulate the establishment and operation of open-end mutual fund investments and protect the legitimate rights of mutual fund investors. In September 2001, the China Securities

Regulatory Commission launched the first open-end mutual fund, "Huaan Innovation." This indicates that the mutual fund industry has evolved from the period of closed-end mutual funds to a period of the open-end mutual funds. It marks the beginning of a new phase of open-end mutual funds. By the end of 2016, there were 108 mutual fund families in China issuing 3867 funds that took the industry size to 9,159.305 billion yuan.[3]

3.1.2 Fund Categories and Annual Summary Statistics

This section introduces basic statistics for the mutual fund market in China. It reports the number of funds, aggregate fund size, fund performance and fund flows by each investment category in China from 2001 to 2016. I collected data from the CSMAR Chinese mutual fund database. The fund categories include equity funds, allocation funds, fixed income funds, convertible funds, alternative funds and commodities funds, as defined by Morningstar. For fund size, it reports the sum of each category. For fund performance and flow, it shows the mean of each category.

3.1.2.1 Fund Size

Table 3-1-1 Annual Summary Statistics for Mutual Fund Size in China

This table reports annual summary statistics for Morningstar global broad categories in China for the period 2001-2016. For each category, the table shows the number of funds and the sum of total net assets by year (in millions of yuan). Fund size is measured on a quarterly basis.

[3]The summary statistics are from Asset Management Association of China (http://www.amac.org.cn/tjsj/xysj/jjgssj/391714.shtml).

Table 3-1-1 (continued)

Year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
			The number of funds			
2001		2				
2002	1	6	1	1		
2003	6	27	9	1		
2004	13	57	11	2		
2005	26	72	13	2		
2006	58	94	20	2		
2007	91	131	21	2		
2008	142	125	44	2		
2009	191	150	68	2		
2010	263	158	75	2		
2011	354	165	100	8		
2012	425	180	120	11		
2013	469	209	214	15		
2014	536	305	257	17	1	2
2015	402	998	303	18	2	5
2016	468	1339	526	19	5	5
All sample years average	230	251	119	7	3	4
Last 10 years average	334	376	173	10	3	4
Last 5 years average	460	606	284	16	3	4
			The sum of total net asset			
year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
2001		1034.78				
2002	238.07	2381.69	449.85	481.28		
2003	1126.53	4736.40	973.06	275.49		
2004	3508.54	14170.97	488.83	445.62		
2005	4666.32	12944.22	2490.02	376.30		
2006	22075.70	30531.82	2090.93	353.32		
2007	170224.19	195519.38	7239.94	766.67		
2008	96596.38	76988.79	17031.90	575.25		
2009	169056.48	114357.99	6647.63	727.94		
2010	167452.43	108654.58	8808.05	978.51		
2011	139143.09	85039.58	10401.28	1815.49		
2012	145421.75	82460.71	16988.81	1593.37		
2013	143654.07	83677.25	19564.77	1534.90		
2014	158744.38	85441.15	25364.21	2113.05	5.61	94.58
2015	78063.93	269002.75	51692.46	855.14	16.90	1671.87
2016	65024.50	209706.23	120929.60	626.29	389.39	233.33
All sample years average	90999.76	86040.52	19410.76	901.24	137.30	666.59
Last 10 years average	133338.12	131084.84	28466.87	1158.66		
Last 5 years average	118181.72	146057.62	46907.97	1344.55		

From Table 3-1-1, in terms of the number of funds, it shows that equity funds have the largest number 536 before 2014. On 8 August 2014, the China Security Regulatory Commission (CSRC) adjusted the minimum requirement of equity funds in equity holdings from 60% to 80%. It made many equity funds to change their type to allocation funds, which have a lower equity holding requirement. In 2016, allocation funds had the largest number 1,339. Fixed income funds grew steadily from 11 in 2004 to 526 in 2016. The table suggests that allocation funds are the largest active investment tool in China, over two times larger than equity fund in terms of fund numbers.

In terms of total net assets, equity funds account for the largest type of funds with a size of 158744.38 million (yuan) before 2015. Equity funds decreased from their peak of 170,224.19 million in 2007 to 65,024.50 million in 2016. Fixed income fund had steady growth from 6647.63 million in 2009 to 120929.60 million in 2016. Allocation funds became the largest type after 2014, reaching 209,706.23 million in 2016.

At the end of 2016, there were 1,339 allocation funds with a size of 209,706.23 million yuan (or 30,195.28 million dollars) and 468 equity funds with a size of 65,024.50 million yuan (or 9,362.78 million dollars).[4] In addition, fixed income funds also account for a considerable portion of industry size. There were 526 fixed income funds with a size of 120,929.60 million yuan (or 17,412.47 million dollars). The table also suggests that fund managers tend to invest with a flexible stock holdings requirement (lower than 80%) by shifting their fund category from

[4] I take the exchange rate of 6.9450 of dollars to yuan from Bloomberg on 30 December 2016 (https://www.bloomberg.com/quote/USDCNY:CUR).

equity fund to allocation fund in China. Allocation funds have the largest size among open-end mutual funds after 2014.

3.1.2.2 Fund Performance

Table 3-1-2 Annual Summary Statistics for Mutual Fund Total Return in China

The table reports annual summary statistics for Morningstar global broad categories in China for the period 2004-2016. For each category, the table shows the equal-weighted mean of fund total returns by year. Fund return is measured on a quarterly basis.

Year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
			The mean of return			
2004	-1.71%	0.28%	-0.10%	-1.21%		
2005	2.68%	2.37%	3.78%	6.90%		
2006	42.43%	37.64%	6.99%	38.26%		
2007	16.50%	15.71%	8.94%	38.55%		
2008	-2.77%	0.72%	7.59%	12.57%		
2009	19.48%	17.79%	5.19%	12.00%		
2010	9.09%	10.22%	3.98%	7.19%		
2011	-5.25%	-2.01%	5.18%	3.13%		
2012	5.94%	4.87%	3.38%	5.31%		
2013	-2.25%	-1.63%	-1.25%	-3.13%		
2014	16.71%	10.61%	8.34%	42.82%	-0.11%	-0.59%
2015	22.99%	23.43%	6.85%	17.11%	-3.13%	0.60%
2016	0.13%	2.08%	0.62%	-3.59%	-7.42%	0.27%
All sample years average	9.54%	9.39%	4.58%	13.53%	-3.55%	0.09%
Last 10 years average	8.06%	8.18%	4.88%	13.20%		
Last 5 years average	8.71%	7.87%	3.59%	11.70%		

From Table 3-1-2, in terms of total fund returns, I find that, on average, the equity fund market offers a positive return of 9.54%. Equity funds offered the highest annual average returns of 42.43% in 2006 and the second highest at 22.99% in 2015. In the last five and ten years, equity funds offered a return of 8.71% and 8.06%. Allocation funds, on average, offer investors 9.39% in all years. They offered the highest return of 37.64% in 2006 and the second highest of 23.42% in 2015. In the last five and ten years, allocation funds provided returns of 7.87% and 8.18%. The table indicates that active funds in China, on average, provide a positive total return of over 8%, which is profitable for investors.

3.1.2.3 Fund Flows

Table 3-1-3 Annual Summary Statistics for Mutual Fund Flow in China

The table reports annual summary statistics for Morningstar global broad categories in China in the period 2004-2016. For each category, the table shows the mean of fund flows by year. Fund flow is measured on a quarterly basis.

Year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
			The mean of flow			
2004	-4.98%	-13.48%	-16.01%	-9.00%		
2005	-3.56%	-5.29%	1.60%	4.29%		
2006	17.93%	3.13%	-26.25%	-16.45%		
2007	-5.36%	-6.70%	63.34%	-65.57%		
2008	-10.21%	-10.99%	14.98%	-16.96%		
2009	-10.52%	-10.49%	-16.78%	-15.93%		
2010	-5.98%	-10.93%	-6.57%	-12.39%		
2011	-2.99%	-3.66%	6.89%	-6.86%		
2012	-3.01%	-3.61%	-3.60%	-15.89%		
2013	0.88%	1.91%	-21.40%	-7.87%		
2014	8.52%	-7.30%	0.57%	88.67%	-32.58%	-41.44%
2015	8.58%	0.73%	27.90%	-6.78%	11.07%	-8.67%
2016	4.48%	0.52%	-4.99%	-4.55%	60.18%	-28.44%
All sample years average	-0.48%	-5.09%	1.51%	-6.56%	12.89%	-26.18%
Last 10 years average	-1.56%	-5.05%	6.03%	-6.41%		
Last 5 years average	3.89%	-1.55%	-0.31%	10.72%		

From Table 3-1-3, in terms of fund flow, I find that, on average, the Chinese mutual fund market experienced money outflows from 2004 to 2016. Equity funds and allocation funds have negative average flows of -0.48% and -5.09% from 2004 to 2016, and they experienced five years of money outflows from 2008 to 2012. Fixed income fund had an average of 1.51% money inflows from 2004 to 2016, and a massive money inflow of 27.9% in 2015. Convertible funds had an average negative flow of -6.56%. In terms of the last ten years' flows, only fixed income funds had a positive flow of 6.03%. Regarding the previous five years' flows, equity funds and convertible funds demonstrated positive flows of 3.89% and 10.72%.

The table indicates that in recent years from 2004 to 2016, on average, the equity funds and allocation funds have experienced money outflows. Also, equity funds receive money inflows and allocations funds have lower outflows in recent five years. It suggests that money might be shifting from active to passive funds like fixed income funds in recent ten years in China. Also, it may indicate a recovery of fund investments after the financial crisis in 2008.

3.1.2.4 Summary of Fund Market Characteristics in China

In sum, for fund numbers, allocation funds, on average, account for the largest numbers in fund investments. The second largest type is equity funds from 2001 to 2016. As for fund size, allocation funds and equity funds, on average, account for the two largest fund sizes of 131,081.84 million yuan and 133,338.12 million yuan in the last decade. Also, for fund performance, active funds on average rewarded investors with a total return of over 8% in the previous decade. Regarding fund flows, active funds on average experienced money outflows from 2004 to 2016. While in the last five years, equity funds experienced money inflows of 3.89% while allocation funds experienced a relatively small outflow of -1.55%. At the end of 2016, for the active funds in the following analysis, 1339 allocation funds reached a size of 209,706.23 million yuan (or 30,195.28 million dollars), and 468 equity funds reached a size of 65,024.50 million yuan (or 9,362.78 million dollars).

3.1.3 Mutual Fund Investors' Characteristics

I investigate investor characteristics in China in this section. I manually collected statistics from the annual Survey Report of Fund Investors for 2010-2014 and the China Securities Investment Funds Fact Book for 2012-2016 from the Asset

Management Association of China. Section 3.1.3.1 reports investor profiles, including profit and loss of mutual fund investors, investor account structure, asset distribution, age, income structure, fund allocation to income, investment experience and holding periods. Section 3.1.3.2 summarizes information supplies and sale institutions. Section 3.1.3.3 shows the purpose of investors in fund purchasing, including the top concerns in fund picking and investment purposes. Section 3.1.3.4 concludes the overall statistics.

3.1.3.1 Mutual Fund Investors' Profiles in China

Table 3-1-4 Profit and Loss of Mutual Fund Investors

This table reports profit and loss for mutual fund investors from 2012 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2012	2013	2014	2015	2016	Average
> 30% loss	19.00%	13.00%	7.00%	13.00%	22.30%	14.86%
0-30% loss	28.00%	22.00%	11.00%	27.20%	23.00%	22.24%
Close to zero	24.00%	27.00%	20.00%	27.10%	23.80%	24.38%
0-30% profit	20.00%	30.00%	40.00%	22.60%	22.20%	26.96%
30%-100% profit	5.00%	7.00%	19.00%	8.00%	6.50%	9.10%
>100% profit	3.00%	1.00%	3.00%	2.20%	2.20%	2.28%
Non-negative profit	52.00%	65.00%	82.00%	59.90%	54.70%	62.72%
Positive profit	28.00%	38.00%	62.00%	32.80%	30.90%	38.34%

Mutual funds in China have rewarded investors with considerable profits in the last five years. From Table 3-1-4, regarding performance, I find that there are 52%, 65%, 82%, 59.9%, and 54.7% of investors who have non-negative returns respectively, from 2012 to 2016. On average, 62.72% of investors have non-negative returns across five years. Investors have positive returns that account for 28%, 38%, 62%, 32.8%, and 30.9%, respectively, from 2012 to 2016. On average, 38.34% of investors have a positive profit, 26.96% of investors have 0%-30% profit, and 11.38% of investors have a greater than 30% profit. It shows that, on average, a large percentage of fund investors has made positive profits in the last five years.

Table 3-1-5 Investor Account Structure in China

This table reports the total accounts (in tens of thousands) and valid accounts (in tens of thousands) of individuals and institutional investors in China in the period 2006-2014. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Total Account	2049.61	14776.83	16846.51	18640.66	19533.39	22986.62	22727.00	28773.46	46408.83	67917.39	94303.67	32269.45
Valid Account	1087.12	9091.34	8459.42	8092.47	7494.94	7973.62	7635.71	8697.12	12741.58	18758.55	26954.59	10635.13
Valid Account/Total account	53.04%	61.52%	50.21%	43.41%	38.37%	34.69%	33.60%	30.23%	27.46%	27.62%	28.58%	38.98%
Individual account	1082.99	9086.80	8454.35	8084.09	7491.45	7968.35	7630.14	8691.34	12733.88	18750.76	26946.09	10629.11
Institutional account	4.13	4.54	5.07	3.76	3.46	5.26	5.57	5.38	7.70	7.80	8.50	5.56
Individual account (%)	99.62%	99.95%	99.94%	99.90%	99.95%	99.93%	99.93%	99.93%	99.94%	99.96%	99.97%	99.91%
Institutional account (%)	0.38%	0.05%	0.06%	0.05%	0.05%	0.07%	0.07%	0.06%	0.06%	0.04%	0.03%	0.08%

Table 3-1-6 Asset Distribution of Individual Investors' Accounts

This table reports the asset distribution of individual investors' account from 2006 to 2015. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

<table>
<tr><th>Year</th><th>2006</th><th>2007</th><th>2008</th><th>2009</th><th>2010</th><th>2011</th><th>2012</th><th>2013</th><th>2014</th><th>2015</th></tr>
<tr><td><10,000 yuan</td><td rowspan="3">89.93%</td><td rowspan="3">94.65%</td><td rowspan="3">97.50%</td><td rowspan="3">96.47%</td><td rowspan="3">96.90%</td><td>61.73%</td><td>58.67%</td><td>60.68%</td><td>67.17%</td><td>62.5%</td></tr>
<tr><td>10,000-50,000 yuan</td><td>30.69%</td><td>32.00%</td><td>29.82%</td><td>23.53%</td><td>24.7%</td></tr>
<tr><td>50,000-100,000 yuan</td><td>4.50%</td><td>5.15%</td><td>5.31%</td><td>5.01%</td><td>6.3%</td></tr>
<tr><td>100,000-500,000 yuan</td><td>8.50%</td><td>4.76%</td><td>2.23%</td><td>3.18%</td><td>2.82%</td><td>2.77%</td><td>3.66%</td><td>3.72%</td><td>3.78%</td><td>5.6%</td></tr>
<tr><td>>500,000 yuan</td><td>1.57%</td><td>0.60%</td><td>0.27%</td><td>0.35%</td><td>0.28%</td><td>0.31%</td><td>0.52%</td><td>0.47%</td><td>0.51%</td><td>1.0%</td></tr>
</table>

Individual investors are the main participants in the China mutual fund market. For investor accounts, Table 3-1-5 shows that most valid accounts are held by individual investors, who accounts for over 99% from 2006 to 2016. The total accounts showed rapid growth from 227.27 million in 2012 to 943.0367 million in 2016. For the asset held by investors, Table 3-1-6 shows that small investors with assets of less than 10,000 yuan are the largest percentage of investors. Small investors with less than 10,000 yuan of assets increased from 58.67% in 2012 to 67.17% in 2014 and dropped to 62.5% in 2015. Meanwhile, individuals with less than 50,000 of assets invested in mutual fund accounted for 87.2% of investors in 2015. It suggests that individual and small investors are the main participants in the China fund market, while institutional investors have a relatively lower number of accounts.

Table 3-1-7 Age and Investor Account Structure

This table reports the age, investor account structure and market value held by each age group from 2010 to 2015. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Panel A: Age and investor account

Year	2010	2012	2013	2014	2015	Average
Under 30	11.75%	8.00%	17.58%	32.09%	19.40%	17.76%
Age 30-40	28.31%	24.00%	23.49%	24.43%	25.60%	25.17%
Age 40-50	31.97%	33.00%	27.85%	21.62%	26.00%	28.09%
Age 50-60	17.35%	20.00%	17.35%	12.96%	16.60%	16.85%
Above 60	10.62%	15.00%	13.73%	8.91%	12.40%	12.13%

Panel B: Age and market value held by investors

Year	2010	2012	2013	2014	2015	Average
Under 30	6.09%	4.00%	7.30%	11.48%	5.70%	6.91%
Age 30-40	21.89%	18.00%	19.16%	22.05%	18.00%	19.82%
Age 40-50	35.05%	36.00%	30.95%	28.91%	31.00%	32.38%
Age 50-60	21.61%	23.00%	23.26%	20.84%	24.10%	22.56%
Above 60	15.35%	19.00%	19.34%	16.72%	21.10%	18.30%

In Table 3-1-7, it shows that investors aged 40-50 years own the largest number of accounts and hold the largest market value in the Chinese mutual fund market. Regarding the investor accounts in Panel A, investors aged under 30 reach a peak of 32.09% for mutual fund accounts in 2014. By the end of 2015, investors aged between 40 and 50 years had the largest percentage at 26%. On average, investors aged 40-50 years have the highest percentage of 28.09% in the China mutual fund market. Investors aged less than 50 are averagely 71.02% of the China fund market. Regarding the market value in Panel B, investors aged 40-50 years reached the top market value of 36% in 2012. By the end of 2015, investors aged 40-50 years held the largest market value of 31%. On average, investor aged between 40 and 50 years have the largest market value of mutual fund accounts at 32.38%.

Table 3-1-8 Income Structure of Mutual Fund Investors

This table reports the income structure of the mutual fund investors from 2013 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2013	2014	2015	2016	Average
<50 thousand	26.00%	26.00%	23.30%	28.40%	25.93%
50-100 thousand	37.00%	39.00%	40.40%	42.70%	39.78%
100-150 thousand	22.00%	20.00%	20.30%	16.00%	19.58%
150-500 thousand	11.00%	11.00%	12.50%	9.80%	11.08%
>500 thousand	4.00%	4.00%	3.50%	3.10%	3.65%

Investors with moderate and lower incomes (below 150,000 yuan) are the primary participants in the China mutual fund market. In Table 3-1-8, it shows that there is a growing number of small investors with an income of 50,000-100,000 who put their money in the mutual fund market, while wealthy investors with an income over 500,000 thousand tend to withdraw their money from the mutual fund market. By the end of

2016, small investors with an income of 50,000-100,000 were the most substantial participants (42.7%) of the Chinese mutual fund market. On average, fund investors with an income of less than 150,000 yuan are the main participants (85.29%) in China.

Table 3-1-9 Fund Allocation to Incomes of Mutual Fund Investors

This table reports the fund allocation to incomes of mutual fund investors from 2013 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2013	2014	2015	2016	Average
<10%	21.00%	19.00%	23.10%	23.80%	21.73%
10%-30%	30.00%	31.00%	36.80%	39.00%	34.20%
30%-50%	31.00%	27.00%	24.30%	24.20%	26.63%
50%-70%	16.00%	14.00%	9.40%	8.70%	12.03%
>70%	2.00%	9.00%	6.50%	4.30%	5.45%

Table 3-1-10 Investment Experience of Mutual Fund Investors

This table reports the investment experience of mutual fund investors from 2013 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2013	2014	2015	Year	2016
<6 months	10.00%	12.00%	14.90%	<1 year	16.20%
0.5-1 year	13.00%	14.00%	11.20%	1-3 years	26.20%
1-2 years	17.00%	15.00%	20.20%	3-5 years	20.20%
2-5 years	19.00%	17.00%	12.90%	5-10 years	19.10%
>5 years	41.00%	42.00%	40.80%	>10 years	18.30%

The majority of investors allocate no more than 30% of their incomes to the mutual fund market. From Table 3-1-9, by the end of 2016, investors allocated 10%-30% of their incomes to mutual funds, accounting for the largest percentage of 39%. On average, 34.2% of investors allocated 10-30% of their incomes to the mutual fund market from 2013 to 2016; 21.73% of investors invest no more than 10% of their incomes in mutual fund markets. In Table 3-1-10, it shows that investors had no more than five years of investment experience, accounting for the largest percentage of investors (approximately 59%) in the mutual fund market from 2013 to 2015. By the end of 2016, investors with no more than five years of experience accounted for 62.2% of overall market investors.

Table 3-1-11 Holding Periods of Mutual Fund Investors

This table reports the holding periods of mutual fund investors from 2012 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2012	2013	2014	2015	2016	Average
Less than 6 months	9.00%	13.00%	18.00%	21.60%	16.80%	15.68%
6 months - 1 year	16.00%	22.00%	26.00%	23.10%	26.30%	22.68%
1 year - 3 years	34.00%	32.00%	23.00%	25.40%	32.60%	29.40%
3 years - 5 years	25.00%	18.00%	16.00%	16.70%	15.10%	18.16%
More than 5 years	16.00%	15.00%	17.00%	13.10%	9.20%	14.06%

The majority of mutual fund investors in China are short-term investors with an investment horizon of less than three years. From Table 3-1-11, it shows that, on average, the majority of investors (29.4%) hold their mutual fund investments for 1 to 3 years. There is also an increasing trend for investors to keep their investments of less than six months from 9% in 2012 to 16.8% in 2016. By the end of 2016, investors with 1-3 years' investment experience accounted for the largest percentage at 32.6%. On average, investors held their investments for less than three-year accounting for 67.76% of investors on aggregate.

3.1.3.2 Information Supply of Mutual Fund Investors

Table 3-1-12 Information Supply of Mutual Fund Investors

This table reports the information supply of mutual fund investors from 2009 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2009	2010	2012	2013	2014	2016	Average
Financial managers in banks				16%	14%	28.4%	19.6%
Newspapers	13%	10%	8%	9%	13%	22.5%	12.5%
Televisions	3%	8%	5%	4%	11%	10.0%	6.8%
Internet	67%	65%	70%	58%	26%	24.3%	51.7%
Friends and colleagues	11%	10%	9%	8%	11%	4.3%	8.9%
Mobile media				2%	13%	6.2%	7.1%
Investment consultants or analysts					6%	2.2%	4.2%
Broadcasting	2%	3%	3%				2.7%
Other	4%	4%	5%	3%	6%	2.0%	3.9%

The Internet is the leading source for investors obtaining information about mutual funds. From Table 3-1-12, I find that, in 2016, the majority of investors (28.4%) receive investment information about mutual funds from financial managers in banks. The second largest channel to obtain information is internet (24.3%). The third channel is newspapers, which accounts for 22.5%. On average, from 2009 to 2016, investors mainly utilize the internet (51.7%), financial managers (19.6%) and newspapers (12.5%) to obtain relevant investment information about mutual funds.

Table 3-1-13 Sale Institutions for Mutual Fund Investors

This table reports the percentages of investors purchasing mutual funds from sale institutions from 2012 to 2014. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2012	2013	2014	Average
Banks	41%	36%	35%	37%
Securities companies	14%	11%	14%	13%
Fund companies	42%	40%	34%	39%
Independent sales institutions	4%	5%	6%	5%
Online platforms		8%	11%	10%

The main institutions for the fund purchases of mutual fund investors are banks, fund companies and securities companies (brokers). From Table 3-1-13, it shows that the investors mainly purchase mutual funds from banks, fund companies and security companies. By the end of 2014, purchasing from banks accounted for the largest percentage (35%) of fund purchasing. Fund companies account for the second largest percentage of fund purchasing (34%). On average, investors mainly purchase from fund companies (39%), banks (37%) and securities companies (13%).

3.1.3.3 Purpose of Fund Purchasing

Table 3-1-14 Top Concerns of the Fund Purchasing of Mutual Fund Investors

This table reports the concerns in fund purchasing of mutual fund investors from 2010 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2010	2012	2013	2014	2015	2016	Average
Fund performance	25%	44%	59%	28%	67.1%	45.2%	44.7%
Fund company reputation	17%	18%	12%	14%	10.9%	20.3%	15.3%
Return rankings	13%	9%					11.0%
Funds' investment strategies	11%	7%	4%	9%	5.1%	3.2%	6.6%
Dividends	8%	5%	4%	6%	1.4%	1.8%	4.4%
Star fund managers	7%	4%	2%	7%	1.1%	1.8%	3.8%
Net asset value	6%	6%	3%	6%	1.9%	2.4%	4.2%
Fund ratings	6%	3%	1%	5%	0.8%	1.4%	2.8%
Fees	5%	2%	2%	6%	1.1%	1.7%	3.0%
Promotion	1%	0%					0.5%
Recommended by others		1%	1%	1%	0.4%	0.9%	0.9%
Recommended by customer managers in banks		1%					1.0%
Has a foreign shareholder background			3%	4%	3.8%	11.0%	5.4%
Fund company size			5%	8%	3.2%	5.5%	5.4%
Is it a new fund?			3%	2%	1.6%	3.3%	2.5%
Withdraw easily			1%	4%	1.0%	1.3%	1.9%
Other			0%	0%	0.5%	0.3%	0.3%

Fund performance, fund company reputation and funds' investment strategies are the main concerns in their fund purchasing. From Table 3-1-14, it shows that, in 2016, performance and fund company reputation were the main concerns of investors, accounting for 45.2% and 20.3%. Interestingly, in 2016, foreign shareholder backgrounds ranked third (11%), which might be attributed to the increase in qualified foreign institutional investors (QFII) in China. On average, investors are mainly aware of fund performance (44.7%), fund company reputation (15.3%) and funds' investment strategies (6.6%).

Table 3-1-15 Purpose of Fund Purchasing of Mutual Fund Investors

This table reports the purpose in fund purchasing of the mutual fund investors from 2013 to 2016. The statistics are from the Survey Report of Fund Investors and the China Securities Investment Funds Fact Book by the Asset Management Association of China.

Year	2013	2014	2015	2016	Average
Obtain higher returns than interest rate at banks	58%	34%	78.9%	56.0%	57%
Education saving	9%	14%	27.0%	16.0%	17%
Retirement saving	9%	20%	43.4%	15.8%	22%
Diversifying risk	21%	23%	47.3%	9.2%	25%
Other	3%	9%	15.4%	3.0%	8%

Obtaining higher returns is the primary purpose of mutual fund investments in China. From Table 3-1-15, by the end of 2016, obtaining higher returns was the top purpose for investors with a percentage of 56%. On average, 57% of investors regarded earning higher profits than from interest rates as their main purpose. Also, there are 25%, 22%, and 17% of investors who purchase mutual funds for diversifying risk, retirement savings and educating savings.

3.1.3.4 Summary of Investor Profiles in China

In conclusion, mutual fund investors in China are individual and small investors aged below 50 years, with moderate and lower incomes below 150,000 yuan. They like to invest less than 50,000 yuan which accounts for less than 30% of their total assets in the mutual fund market. The majority of them are short-term investors who hold mutual funds for less than three years. They mainly obtain information from the internet and purchase funds from banks, fund companies and securities companies (or brokers). The main concerns in their fund purchasing are fund performance and the reputation of fund companies. The primary purpose of their fund investing is to obtain a higher return than interest rates.

3.2 US Mutual Fund Industry

3.2.1 Brief History of the US Mutual Fund Market

Taking roots from European countries, closed-end mutual funds were launched in the US in the early 1890s. The first closed-end mutual fund – Boston Personal Property Trust, was established in 1893. With the rapid development of closed-end mutual funds, the establishment of the Alexander Fund in Philadelphia in 1907 that allowed investors to withdraw biannually, which promoted the arrival of open-end mutual funds (McWhinney, 2018).

The first open-end mutual fund in the modern world "The Massachusetts Investors Trust", was launched in Boston, US, on 21 March 1924. It required initial capital of 50,000 dollars and provided investors a portfolio constructed of 45 stocks. This fund went public later in 1928. It consistently reported the current fund price to investors, and it allowed them to withdraw their money. In 1929, the US market had 19 open-end mutual funds competing with about 700 closed-end mutual funds (Loth, no date). The ten-year recession after 1929 was a great shock to the development of the US mutual fund industry. It prompted a series of laws to protect the interests of investors, including the Securities Act of 1933, the Security Exchange Act of 1934 and the Investment Company Act of 1940.

The market slowly recovered after the recession, and the number of open-end mutual funds reached 100 in the 1950s. Market confidence gradually returned until 1950 with open-end mutual funds increasing from about 100 in the 1960s to about 360 in the 1970s. The bull market in the 1980s and 1990s accelerated the growth of mutual funds to over 3,000 with assets reaching over one trillion dollars. In recent decades, the industry kept growing with total net assets increasing from 5,525 billion dollars in 1998 to 16,344 billion dollars in 2016.

3.2.2 Fund Categories and Annual Summary Statistics

This section reports basic statistics for the fund market in the US. It describes the number of funds, aggregate fund size, aggregate fund performance and aggregate fund flows by each fund category from 1970 to 2016. The data are downloaded from the Morningstar Direct database. The categories include equity funds, allocation funds, fixed-income funds, convertible funds, alternative funds and commodities funds, as defined by Morningstar. Funds are recognized by the identifier "FUNDID" at the fund level in Morningstar. For fund size, I report the mean and sum of each category. For fund performance and fund flows, it states the mean of each fund category.

3.2.2.1 Fund Size

Table 3-2-1 Annual Summary Statistics for Mutual Fund Size in the US

The table reports annual summary statistics for Morningstar global broad categories in the US in the period 1970-2016. For category, the table shows the number of funds and the sum of total net assets (in millions of dollars). Fund size is measured on a monthly basis.

Table 3-2-1 (continued)

Year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
			The number of funds			
1970	4					
1971	4					
1972	4	1	1			
1973	4	1	1			
1974	7	1	3	1		
1975	8	1	5	1		
1976	186	35	37	3	1	
1977	206	36	65	3	1	
1978	213	38	91	3	3	
1979	229	38	106	3	3	
1980	232	39	117	3	3	
1981	255	40	124	3	3	
1982	279	42	138	3	3	
1983	311	46	168	3	3	
1984	372	48	249	3	3	
1985	431	54	333	6	4	
1986	535	66	451	12	4	
1987	629	81	631	15	4	
1988	714	106	735	20	5	
1989	764	122	786	20	8	
1990	861	134	886	20	11	
1991	947	140	988	20	11	
1992	1053	154	1158	17	12	
1993	1340	195	1553	18	15	
1994	1629	244	1884	19	17	
1995	1858	288	1995	19	19	
1996	2096	323	1996	19	20	
1997	2434	374	1990	21	21	1
1998	2812	404	2031	21	34	1
1999	3161	424	2038	20	43	1
2000	3527	433	2072	22	61	1
2001	3671	469	1988	23	80	1
2002	3677	498	1816	23	86	2
2003	3695	558	1833	24	92	2
2004	3705	640	1853	25	111	3
2005	3837	729	1879	25	139	7
2006	4014	817	1894	24	167	8

Table 3-2-1 (continued)

2007	4174	961	1910	20	191	10
2008	4291	1068	1865	20	214	15
2009	4172	1141	1816	21	240	16
2010	3941	1136	1774	18	285	24
2011	3989	1200	1829	19	356	30
2012	3988	1291	1842	16	421	37
2013	3980	1368	1898	16	474	40
2014	4023	1454	1968	17	557	41
2015	4121	1545	2032	21	606	43
2016	4087	1539	2038	20	553	42
All sample years average	1924.89	451.60	1174.82	15.12	119.12	16.25
Last 10 years average	4076.60	1270.30	1897.20	18.80	389.70	29.80
Last 5 years average	4039.80	1439.40	1955.60	18.00	522.20	40.60

			The sum of total net asset			
year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
1970	55.76					
1971	93.37					
1972	160.09	0.10	2.80			
1973	131.94	0.08	3.18			
1974	183.39	0.05	50.54	44.96		
1975	246.42	0.13	260.13	51.80		
1976	28686.48	6920.86	3429.84	219.22	89.85	
1977	26214.67	6085.60	6049.58	199.43	94.19	
1978	27163.84	5733.81	8911.59	184.26	94.60	
1979	31333.49	5433.81	9524.84	191.85	148.72	
1980	39610.70	5402.59	10380.89	221.37	210.49	
1981	38250.23	4835.64	10836.54	213.99	220.69	
1982	48406.19	5575.72	19495.39	230.85	264.31	
1983	70259.26	6435.63	30945.24	291.13	298.37	
1984	75441.66	7011.52	45444.14	294.89	280.39	
1985	103020.44	11051.88	109098.72	869.95	303.51	
1986	137174.01	18787.35	223213.87	3815.27	267.52	
1987	148838.02	25736.94	231889.84	3483.57	468.62	
1988	161898.01	29014.33	245240.88	2952.88	2057.76	
1989	210607.51	36820.37	259048.89	2601.60	2502.31	
1990	206229.99	35726.38	268162.00	1760.20	2517.18	
1991	311282.96	52086.53	357466.29	1849.87	2548.83	

Table 3-2-1 (continued)

1992	405326.73	77756.87	454309.24	2359.56	2199.88	
1993	602141.13	128668.12	577360.01	3597.66	2408.40	
1994	693588.87	143552.49	499980.28	3489.87	2638.15	
1995	1020745.11	186594.87	568415.92	4415.93	3281.74	
1996	1407396.59	224858.95	592006.61	5630.04	5088.02	
1997	1949223.19	285661.29	665634.56	6610.80	7623.78	90.31
1998	2419059.13	327319.32	755143.45	6088.54	10086.65	71.13
1999	3311809.81	340021.58	741574.37	6910.28	12374.07	129.01
2000	3218710.78	325828.74	736429.04	7370.15	11191.92	22.08
2001	2851070.10	359078.43	858197.97	7374.42	11509.04	15.93
2002	2240310.56	348694.95	1040698.07	7031.79	13594.32	257.81
2003	3140043.64	505222.93	1146500.30	9937.45	18983.92	1724.37
2004	3752732.24	673428.43	1193715.39	10139.80	26711.52	7187.94
2005	4252019.31	836417.69	1250486.15	8618.94	31920.06	15071.92
2006	5110923.49	1063053.59	1383132.42	8781.85	39765.56	15618.80
2007	5683836.98	1275868.01	1544040.12	9903.10	47202.22	17480.44
2008	3214228.49	913626.20	1441638.63	7103.20	41913.56	9803.95
2009	4277708.37	1186148.75	2036739.28	11527.26	56720.32	25208.85
2010	4946338.98	1403392.63	2380610.78	13761.04	78977.60	47189.22
2011	4608964.99	1462969.49	2618490.52	12732.21	93549.13	50030.63
2012	5231185.24	1748043.42	3144031.80	11305.11	115626.76	51134.32
2013	6964277.99	2154456.01	3054032.00	15848.34	174455.08	39894.39
2014	7508515.17	2369151.77	3236254.34	18219.26	191507.88	30488.74
2015	7378423.37	2346828.72	3207721.43	15026.84	181392.47	20269.51
2016	7787694.43	2495380.96	3453749.20	13270.70	173058.35	26956.54
All sample years average	2034926.88	520992.97	898229.93	5733.28	33320.68	17932.29
Last 10 years average	5760117.40	1735586.60	2611730.81	12869.71	115440.34	31845.66
Last 5 years average	6974019.24	2222772.17	3219157.75	14734.05	167208.11	33748.70

From Table 3-2-1, in term of the number of funds, on average, equity funds have the largest number at 1,924.89 across all years from 1970 to 2016, reaching 4,087 at the end of 2016. Fixed income funds have the second largest number reaching 2,038 in 2016. In terms of total net assets, equity funds account for the largest size of 7,787,694.43 million dollars at the end of 2016. It accounts for the largest fund category across the period 1970-2016, while fixed-income funds rank the second (3,453,749.20

million) and allocation funds (2,495,380.96 million) third. Recent years have also witnessed a steady increase in the size of equity funds and allocation funds, from 2008 to 2016. The statistics show that equity fund is the main investment tool in the US, accounting for the largest proportion of market shares. The growth in the size of equity funds also indicates the prosperous development of the US mutual fund market.

3.2.2.2 Fund Performance

Table 3-2-2 Annual Summary Statistics for Mutual Fund Return in the US

The table reports annual summary statistics for Morningstar global broad categories in the US in the period 1970-2016. For each category, I calculate the mean of fund returns at the end of each year. Fund return is measured on a monthly basis.

Year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
			The mean of fund return			
1970	4.01%					
1971	1.90%					
1972	-0.49%	-0.60%	0.71%			
1973	0.67%	-0.60%	0.71%			
1974	-0.30%	-0.60%	-2.00%	-2.26%		
1975	1.54%	-0.60%	0.05%	1.07%		
1976	4.49%	3.08%	1.65%	3.86%	4.92%	
1977	1.97%	1.70%	0.46%	1.31%	4.92%	
1978	2.52%	1.36%	0.04%	1.54%	2.21%	
1979	3.25%	1.53%	0.53%	2.11%	2.98%	
1980	0.71%	0.66%	-0.07%	0.20%	1.10%	
1981	0.05%	0.35%	-1.50%	0.17%	0.29%	
1982	1.69%	1.70%	1.37%	1.42%	0.35%	
1983	0.76%	1.01%	0.38%	0.49%	1.01%	
1984	1.08%	0.62%	0.92%	0.88%	1.05%	
1985	1.96%	1.60%	1.56%	2.04%	2.21%	
1986	0.21%	0.58%	0.56%	-0.29%	0.11%	
1987	2.75%	1.44%	0.56%	2.00%	1.96%	
1988	2.14%	1.59%	0.63%	1.76%	2.57%	
1989	1.64%	1.11%	0.55%	0.81%	1.26%	
1990	0.77%	0.58%	0.51%	0.63%	1.63%	
1991	2.24%	1.63%	1.14%	1.63%	1.23%	

Table 3-2-2 (continued)

1992	0.58%	0.61%	0.72%	1.20%	0.27%	
1993	1.36%	1.06%	0.84%	1.29%	0.89%	
1994	-0.01%	-0.14%	-0.28%	-0.20%	0.08%	
1995	1.88%	1.69%	1.15%	1.60%	1.21%	
1996	1.39%	1.03%	0.37%	1.15%	0.63%	
1997	1.40%	1.40%	0.65%	1.32%	0.66%	-1.07%
1998	1.09%	1.08%	0.49%	0.57%	0.38%	-2.85%
1999	2.18%	0.92%	-0.06%	2.33%	0.53%	2.49%
2000	-0.09%	0.25%	0.65%	0.50%	0.13%	2.97%
2001	-0.66%	-0.20%	0.46%	-0.38%	0.13%	-2.89%
2002	-1.51%	-0.69%	0.61%	-0.62%	-0.55%	2.04%
2003	2.46%	1.50%	0.55%	1.92%	1.10%	1.90%
2004	1.12%	0.75%	0.38%	0.80%	0.45%	1.34%
2005	0.81%	0.50%	0.24%	0.36%	0.42%	1.80%
2006	1.23%	0.90%	0.43%	0.83%	0.57%	-0.23%
2007	0.72%	0.55%	0.34%	0.79%	0.32%	1.73%
2008	-3.56%	-2.34%	-0.47%	-2.71%	-1.73%	-3.53%
2009	2.54%	1.77%	1.19%	2.78%	0.54%	1.54%
2010	1.46%	0.98%	0.49%	1.38%	0.25%	1.30%
2011	-0.25%	-0.01%	0.52%	-0.13%	-0.30%	-0.56%
2012	1.25%	0.91%	0.60%	0.93%	0.17%	-0.05%
2013	1.95%	1.12%	-0.05%	1.61%	0.41%	-0.68%
2014	0.49%	0.40%	0.39%	0.58%	0.15%	-1.35%
2015	-0.11%	-0.14%	0.02%	-0.12%	-0.18%	-1.90%
2016	0.83%	0.58%	0.34%	0.62%	0.04%	0.88%
All sample years average	1.15%	0.73%	0.43%	0.88%	0.89%	0.14%
Last 10 years average	0.53%	0.38%	0.34%	0.57%	-0.03%	-0.26%
Last 5 years average	0.88%	0.58%	0.26%	0.73%	0.12%	-0.62%

From Table 3-2-2, in terms of total fund returns, I find that, on average, the US mutual fund market offers returns close to zero. In the last ten years, equity funds provided the highest annual average return of 2.54% in 2009, and the allocation fund had the highest return of 1.77% in 2009. Equity fund and allocation fund, on average, offered investors 0.53% and 0.38% in the last decade. In the last five years, there has been a slight increase in the total return. The average total return is 0.88% for equity funds and 0.58% for allocation funds. The statistics are consistent with the literature showing that the US market on average provides a premium close to zero (Gruber, 1996; Berk and Green, 2004).

3.2.2.3 Fund Flows

Table 3-2-3 Annual Summary Statistics for Mutual Fund Flows in the US

The table reports annual summary statistics for Morningstar global broad categories in the US in the period 1971-2016. For each category, I calculate the mean of fund flows at the end of each year. Fund flow is measured on a monthly basis.

Year	Equity	Allocation	Fixed Income	Convertible	Alternative	Commodities
			The mean of fund flows			
1970	5.00%					
1971	13.54%					
1972	15.07%	4.02%	2.18%			
1973	-7.32%	1.49%	0.94%			
1974	-9.27%	-6.32%	12.19%	55.78%		
1975	12.01%	1.68%	16.53%	14.14%		
1976	0.73%	-2.02%	10.82%	7.88%	-1.25%	
1977	-2.58%	-1.90%	7.81%	-4.00%	-0.64%	
1978	1.52%	0.05%	8.98%	-2.70%	-2.32%	
1979	3.42%	-2.71%	8.60%	0.21%	4.59%	
1980	13.72%	3.27%	3.89%	11.85%	40.51%	
1981	3.44%	-2.66%	6.53%	0.28%	3.15%	
1982	8.33%	5.25%	17.01%	-7.36%	8.85%	
1983	12.82%	7.32%	12.93%	10.84%	7.03%	
1984	-0.33%	1.54%	6.06%	0.64%	-1.79%	
1985	10.87%	13.14%	17.99%	15.43%	4.02%	
1986	10.60%	13.65%	22.71%	27.27%	3.62%	
1987	3.86%	5.09%	7.57%	1.05%	13.57%	
1988	1.16%	2.52%	7.13%	-2.22%	4.74%	
1989	7.68%	8.09%	7.03%	2.34%	8.36%	
1990	1.77%	2.09%	5.29%	-6.26%	6.11%	
1991	4.79%	3.34%	5.72%	0.54%	1.89%	
1992	4.88%	6.04%	5.64%	2.99%	3.61%	

Table 3-2-3 (continued)

1993	4.81%	4.42%	4.67%	4.04%	0.90%	
1994	3.10%	3.79%	1.17%	0.75%	1.44%	
1995	2.74%	2.80%	0.92%	0.38%	2.17%	
1996	3.64%	2.95%	0.71%	0.62%	3.14%	
1997	3.17%	2.64%	0.92%	0.71%	2.09%	23.28%
1998	2.33%	2.24%	1.32%	-2.56%	1.93%	1.33%
1999	2.00%	0.95%	0.36%	0.98%	0.69%	-0.47%
2000	2.27%	0.53%	-0.19%	1.67%	3.36%	0.93%
2001	1.67%	2.31%	1.07%	-0.13%	4.23%	0.13%
2002	1.26%	2.80%	1.62%	1.35%	5.02%	19.49%
2003	1.99%	3.79%	0.84%	3.50%	5.91%	12.96%
2004	1.40%	5.20%	0.14%	-0.01%	3.21%	9.04%
2005	1.35%	5.01%	0.22%	-2.07%	3.69%	7.51%
2006	1.37%	4.46%	0.30%	-1.15%	3.71%	3.45%
2007	1.00%	4.22%	0.56%	0.65%	2.26%	4.17%
2008	0.27%	2.70%	0.17%	0.29%	3.27%	3.30%
2009	0.38%	2.42%	1.38%	0.65%	4.95%	5.30%
2010	0.65%	2.32%	1.11%	0.40%	4.06%	5.27%
2011	0.62%	1.92%	0.88%	0.62%	4.48%	3.95%
2012	0.47%	2.35%	1.43%	-0.91%	2.92%	2.81%
2013	1.12%	2.34%	0.24%	0.72%	3.11%	0.92%
2014	0.68%	1.78%	0.69%	2.73%	2.36%	1.77%
2015	0.29%	1.64%	0.17%	0.62%	1.06%	1.50%
2016	-0.17%	1.30%	0.46%	0.31%	-0.23%	1.82%
All sample years average	3.28%	2.89%	4.77%	3.32%	4.24%	5.42%
Last 10 years average	0.53%	2.30%	0.71%	0.61%	2.82%	3.08%
Last 5 years average	0.48%	1.88%	0.60%	0.69%	1.84%	1.76%

From Table 3-2-3, in terms of fund flows, it shows that, on average, the US mutual fund market has experienced steady inflows in the last decade. Equity funds and allocation funds have had positive average flows of 3.28% and 2.89% across all periods, and they have experienced money inflows steadily from 2009 to 2015. In the last decade, allocation funds have had an average inflow of 2.30% which is higher than 0.53% for equity funds. Notably, alternative funds have had the highest inflow of 2.82%. Fixed income had an inflow of 0.71%. Overall, it shows that the US mutual fund market still attracts new money flows in active management fund sectors. It implies that although the active mutual fund market, on average, does not provide very profitable premium, skilled investors might have sophisticated ways to identify superior funds (Gruber, 1996; Barber, Huang and Odean, 2016).

3.2.2.4 Summary of Fund Market Characteristics in the US

In sum, the statistics show that equity funds account for the largest size and largest fund numbers across all fund categories in the US mutual fund market from 1970 to 2016. In 2016, the number of equity funds had reached 4,087 and allocation funds 1,539. Regarding fund performance, equity funds and allocation funds have offered returns of 0.53% and 0.38% in the last decade. Regarding fund flows, US active funds have experienced steady inflows. Equity funds and allocation funds had average inflows of about 0.53% and 2.30% in the last decade. The statistics imply that US investors might have the ability to identify superior fund even though the active mutual fund sector does not appear to offer high premiums (Gruber, 1996). Sophisticated investors might employ more advanced benchmarks in their fund picking (Barber, Huang and Odean). The statistics might also suggest the existence of smart money effects in the US market (Zheng, 1999; Keswani and Stolin, 2008).

3.2.3 Mutual Fund Investors' Characteristics in the US

I report investor characteristics in the US in this section. I manually collected data from the US Investment Company Fact Book 2012-2017 from the Investment Company Institute. In these documents, data before 2014 are recorded by the May of each year;

data after 2014 (include 2014) are recorded by the middle of each year. Section 3.2.3.1 presents investor profiles, including the percentage of US households that own mutual funds, age and mutual fund ownership, household incomes and mutual fund ownership, household incomes of mutual fund owners. Section 3.2.3.2 shows the information supply of investors, including the source of their fund purchasing and shareholders' views on the mutual fund industry. Section 3.2.3.3 summarizes the purposes of fund investments and investors' willingness to take risks. Section 3.2.3.4 concludes these statistics.

3.2.3.1 Mutual Fund Investors' Profiles in the US

Table 3-2-4 Percentage of US Households that Own Mutual Funds

This table reports the mutual fund ownership of US households from 1980 to 2016. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Year	Percentage
1980	5.7
1985	14.7
1990	25.1
1995	28.7
2000	45.7
2005	44.4
2010	45.3
2011	44.1
2012	44.4
2013	46.3
2014	43.3
2015	43
2016	43.6

Table 3-2-5 Age and Mutual Fund Ownership

This table reports the percentages of households owning mutual funds within each age group and the whole mutual fund ownership by generation groups. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Panel A:

Year	2011	2012	2013	2014	Year	2015	Year	2016
<35	32%	34%	31%	34%	18-34	32%	18-35	35%
35-44	52%	52%	49%	49%	35-50	50%	36-51	50%
45-54	52%	53%	60%	53%	51-69	49%	52-70	48%
55-64	50%	52%	58%	50%	>70	33%	>71	33%
>65	37%	34%	37%	34%				

Panel B:

Year	2014	2015	2016	Average
Millennial generation	15%	16%	18%	16%
Generation X	31%	32%	33%	32%
Baby boom generation	42%	40%	38%	40%
Silent and GI generations	12%	12%	11%	12%

From Table 3-2-4, it shows that there is a steadily increasing trend for US households to hold mutual funds from 1980 to 2000. It rose from 5.7% in 1980 to 45.3% in 2000. By mid-2016, approximately 43.6% of US households owned mutual fund. From Table 3-2-5, investors aged about 36-51 years (50%) mostly prefer to buy mutual funds by mid-2016. Also, investors aged about 36-70 years from Generation X and the baby boom generation account for large mutual fund ownership.[5] On average, households aged about 52-70 years (baby boom generation) held the largest percentage of mutual funds (40%) and Generation X aged about 36-51 years had the second largest ownership of US mutual funds (32%) by the mid of 2016.

[5] Silent and GI Generations were born between 1904 to 1945. Baby boom generation was born between 1946 and 1964. Generation X was born between 1965 and 1980. Millennial generation was born between 1981 and 2004. The definitions are from the US Investment Company Fact Book.

Table 3-2-6 Household Incomes and Mutual Fund Ownership

This table reports the percentages of mutual fund ownership of US investors within each income group. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Year	2011	2012	2013	2014	2015	2016	Average
>$100000	81%	81%	81%	77%	78%	80%	80%
$75000-$99999	67%	71%	67%	67%	61%	60%	66%
$50000-$74999	52%	53%	55%	52%	47%	46%	51%
$35000-$49999	32%	36%	39%	36%	34%	29%	34%
$25000-$34999	29%	25%	27%	21%	21%	18%	24%
<$25000	12%	8%	12%	7%	9%	9%	10%

Table 3-2-7 Household Incomes of Mutual Fund Owners

This table reports the incomes of US households owning mutual funds. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Year	2012	2013	2014	2015	2016	Average
>$200,000	8%	8%	9%	11%	11%	9%
$100,000-$199,999	31%	30%	31%	34%	38%	33%
$75,000-$99,999	18%	17%	19%	16%	16%	17%
$50,000-$74,999	21%	21%	21%	19%	18%	20%
$35,000-$49,999	11%	12%	11%	10%	8%	10%
$25,000-$34,999	6%	6%	5%	5%	4%	5%
<$25,000	5%	6%	4%	5%	5%	5%

Households with higher incomes are more willing to own mutual funds. From Table 3-2-6, it is suggested that mutual fund ownership increases with the growth in household incomes. In mid-2016, only 9% of households with less than 25,000 dollars of annual incomes owned mutual funds, while 80% of households held mutual funds when their incomes exceeded 100,000 dollars.

The majority of mutual fund investors are households with lower or moderate incomes. From Table 3-2-7, on average, it shows that nearly 57% of mutual funds were held by US households with less than 99,999 dollars of incomes. US households with higher incomes showed an increasing trend to own mutual funds. Households with more than 200,000 dollars increased from 8% in 2012 to 11% in 2016. In addition, households with an income between 100,000 and 199,000 increased their weight from 31% in 2012 to 38% in 2016. Households with less than 100,000 dollars of incomes showed a decreasing trend to own. Also, households with an income of between 50,000 and 74,999 dollars decreased from 21% in 2012 to 18% in 2016.

3.2.3.2 Information Supply of Investors

Table 3-2-8 Source of Fund Purchasing of US Investors

This table reports the source of mutual fund investors for fund purchasing and sources for investors outside employer-sponsored retirement plans. Panel A reports types of mutual fund ownership and Panel B reports sources of fund purchasing. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Panel A: The type of mutual fund ownership

Year	2011	2012	2013	2014	2015	2016	Average
Outside employer-sponsored retirement plans only	31%	28%	19%	18%	20%	19%	23%
Inside and outside employer-sponsored retirement plans	37%	37%	42%	39%	40%	44%	40%
Inside employer-sponsored retirement plans only	32%	35%	39%	43%	40%	37%	38%

Panel B: The source of fund purchasing outside the employer-sponsored retirement plans

Year	2011	2012	2013	2014	2015	2016	Average
Investment professionals and fund companies, fund supermarkets or discount brokers	35%	35%	39%	40%	42%	42%	39%
Fund companies, fund supermarkets, or discount brokers only	12%	11%	12%	13%	15%	12%	13%
Investment professionals only	45%	47%	42%	40%	36%	38%	41%
Source unknown	8%	7%	7%	7%	7%	8%	7%

On average, the majority (over 38%) of US mutual fund owners purchase funds from employer-sponsored retirement plans. From Table 3-2-8, I find that nearly 80% of US investors purchase mutual funds as part of employer-sponsored retirement plans. On average, only 23% of mutual fund investors purchase their shares outside employer-sponsored retirement plans. In terms of sources of the fund for purchasing outside employer-sponsored plans, on average, 41% purchase funds from investment professionals only; 39% purchase from investment professionals and fund companies, fund supermarkets or discount brokers; 13% buy from fund companies, fund supermarkets, or discount brokers only; the remaining 7% buy from unknown sources.

Table 3-2-9 Shareholders View of the Mutual Fund Industry

This table reports the shareholders' view of the mutual fund industry from 2001 to 2016. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Year	2001	2002	2003	2005	2007	2008	2009	2010	2013	2014	2015	2016	Average
Very favourable	22%	16%	15%	15%	20%	16%	10%	12%	13%	17%	16%	13%	15%
Somewhat favourable	57%	55%	59%	59%	57%	57%	54%	55%	55%	51%	51%	52%	55%
Somewhat unfavourable	4%	10%	7%	7%	8%	10%	16%	14%	9%	8%	9%	8%	9%
Very unfavourable	1%	1%	2%	2%	1%	2%	4%	2%	2%	2%	2%	2%	2%
No opinion	16%	18%	17%	17%	14%	15%	16%	17%	21%	22%	22%	25%	18%

In general, US investors have a favourable view of the mutual fund market. From Table 3-2-9, on average, it seems 70% of investors have a positive view of the mutual fund markets. It also shows that 55% of investors hold a somewhat favourable view of the US mutual fund industry which accounts for the largest portion of investors. Investors demonstrated a very favourable view increasing from 10% in 2009 to 17% in 2014; then it decreased from 17% in 2014 to 15% in 2016. Investors with a somewhat favourable view decreased from 54% in 2009 to 52% in 2016. Investors having a somewhat unfavourable view also showed a decreasing trend from 16% in 2009 to 9% in 2016. Investors having a very unfavourable view stayed at 2% in 2016.

3.2.3.3 Purposes of Fund Purchasing

Table 3-2-10 Purposes of Mutual Fund Investors in Fund Purchasing

This table reports the purpose of US investors in fund purchasing of 2015 and 2016. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

Year	2015		2016	
	A financial goal	Primary financial goal	A financial goal	Primary financial goal
Retirement	91%	72%	92%	74%
Emergency	50%	8%	46%	7%
Reduce taxable income	49%	4%	46%	4%
Current income	30%	7%	27%	6%
Education	24%	5%	22%	5%
House or other large items	15%	3%	13%	3%
Other	4%	1%	4%	1%

Investors purchase mutual funds mainly for retirement purposes. From Table 3-2-10, regarding primary financial goals, I find that the primary goal of the mutual fund investment of US households is to save for retirement. In mid-2016, this accounts for 74%, which is far larger than the second and third primary goals – saving for emergencies at 7% and current income at 6%. In terms of a financial goal, retirement saving also ranked the first at 92% in 2016, while emergency purposes (46%) and reduce taxable income (46%) ranked equal second.

Table 3-2-11 Investors' Willingness to Risk-Taking

This table reports investors' willingness to risk-taking in US households, households owning mutual funds and households not owning mutual funds from 2008 to 2016. The statistics are from the US Investment Company Fact Book from the Investment Company Institute.

All US households

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Substantial risk for substantial gain	5%	4%	4%	4%	5%	5%	6%	6%	6%	5%
Above-average risk for above-average gain	18%	15%	15%	15%	14%	16%	15%	15%	15%	15%
Above risk for average gain	37%	37%	37%	35%	35%	36%	35%	33%	33%	35%
Below-average risk for below-average gain	8%	11%	11%	10%	10%	10%	9%	9%	8%	10%
Unwilling to take any risk	32%	33%	33%	36%	36%	33%	35%	37%	38%	35%

Households owning mutual funds

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Substantial risk for substantial gain	6%	5%	5%	4%	5%	4%	6%	6%	7%	5%
Above-average risk for above-average gain	30%	25%	25%	25%	23%	26%	25%	25%	26%	26%
Above risk for average gain	50%	49%	49%	48%	49%	48%	49%	47%	47%	48%
Below-average risk for below-average gain	7%	10%	10%	10%	11%	12%	10%	10%	8%	10%
Unwilling to take any risk	7%	11%	11%	13%	12%	10%	10%	12%	12%	11%

Households not owning mutual funds

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Substantial risk for substantial gain	4%	4%	4%	4%	6%	5%	6%	7%	5%	5%
Above-average risk for above-average gain	7%	7%	7%	6%	6%	6%	7%	7%	6%	7%
Above risk for average gain	26%	27%	27%	25%	23%	26%	24%	22%	20%	24%
Below-average risk for below-average gain	8%	11%	9%	10%	9%	9%	8%	7%	8%	9%
Unwilling to take any risk	55%	51%	53%	55%	56%	56%	55%	57%	61%	55%

Households owning mutual funds are far more willing to take investment risks than other households. From Table 3-2-11, in terms of households with mutual fund ownership, on average, 79% of them have a willingness to take risks for above-average gains or higher gains. However, 55% of households not owning mutual funds show an unwillingness to take any risks. Regarding all US households, on average, approximately 55% of them are willing to take risks above the average or higher gains.

3.2.3.4 Summary of investor characteristics in the US

In conclusion, US mutual funds investors are mainly aged 36 to 70 years from Generation X and the baby-boom generation by the end of 2016. Households with higher incomes are more willing to hold mutual funds. The majority (57%) of US households investing in the mutual fund market have moderate and low incomes of less than 10,000 dollars. They are mainly purchasing mutual funds for retirement saving purpose (74%), and they purchase them as part of retirement plans within employer-sponsored retirement plans (over 38%). On average, 55% of US households have a favorable view of the mutual fund industry. Households with mutual fund ownership are more willing to take risks than other investors (79%).

3.3 Summary of Market Differences Between China and the US

The differences in market structure and investor sophistication between China and the US mutual fund markets provide us with new perspectives on studying the behaviour of mutual funds. According to statistics from the China and US mutual fund market, we summarize the following key differences.

Regarding mutual fund industry characteristics, first, the mutual fund market in China has a relatively short history and small size compared to the US market. Both markets show average inflows to the equity fund sector after the financial crisis in 2008, which might indicate the recovery of the active management fund industry. Second, the mutual fund market in China has generally provided higher premiums than the US market in the last decade. The average market total return in China is over 8%, while the US market offers a return close to zero. As the US market still has steady money inflows in the equity fund sector, it indicates that the smart money effect might be more pronounced in the US market.

As for investor profiles, a list of interesting statistics difference makes these two market worthwhile places to compare and explore the investment preference of mutual fund investors.

First, individual investors are the main participants of the China fund market. Individual or retail investors are the largest stock market participants in China (over 80%), while institutional investors generally have ownership of all accounts below 10%. As the literature develops, Barber and Odean (2000) find that individual investors who trade actively will reduce their wealth. This overconfidence explains the frequent trades by individual investors. In addition, Keswani and Stolin (2008) find that the purchasing behaviour of individual investors contributes to the existence of smart money effects. Motivated by statistics and the literature, the analysis of individual participants versus institutional participants should improve our understanding of fund behaviour studies.

Second, mutual fund investors in China are relatively young and have modest incomes compared to investors in the US market. Mutual fund investors in China are generally aged below 50 years with modest incomes below 150,000 yuan, while in the US relatively rich households with incomes over 50,000 dollars and aged over 50 years (baby boom generation) are more likely to hold mutual funds. Empirically, Barber, Huang and Odean (2016) find that sophisticated investors have advanced benchmarks in their fund picking. Investor sophistication differs between broker-sold or direct-sold channels, high or low sentiment periods, and wealthy or other investors. The investors who utilize direct-sold channels, who are responseless in low sentiment periods and who own more wealth, tend to be sophisticated in their fund investments. Consistent with the literature and industry background, the approach of studying investors in different life stages and different financial states contributes to our knowledge of fund decision research.

Third, mutual fund investors in China tend to rely more on public information for fund purchases as they mainly purchase from banks, fund companies and brokers, while in the US a small portion of investor purchase based on relatively private information. Investors purchasing mutual fund products from banks and securities companies (brokers) account for about 50% of the sale channel in China, while US investors purchasing from brokers and fund supermarkets account on average for about 39% of the overall sale channel. Studies document that the distribution channel does differ with investor sophistication. Chrisoffersen, Evans and Musto (2013) find that payments from mutual funds to brokers significantly affect fund flows. These mutual funds with loads sharing agreements between underwriters and the sale force appear to have poor performance. It implies that direct-sold investor will be more sophisticated and use advanced benchmarks in fund picking compared to broker-sold investors. Gucercio and Reuter (2013) find that direct-sold funds add values for investors by outperforming their benchmarks, while broker-sold funds tend to underperform indexes. Bergstresser, Chalmers and Tufano (2009) find that broker-sold funds generally deliver lower risk-adjusted performance than direct-sold funds. In addition, broker-sold funds are not able to allocate assets efficiently on the aggregate level. Motivated by statistics and prior studies, the investigation of the direct-sold or broker-sold channels will enrich our knowledge of the information criteria of fund investors.

Fourth, investors in China show more speculative and investment purposes in their fund investing, while US investors exhibit more conservative purposes. The purpose of obtaining higher premium ranks top (57%) in China, while the second and third are diversifying risk (25%) and retirement plans (22%). Scholars find that smart money exists as investors successfully identify well-performing funds. Gruber (1996) finds that mutual fund investors show the ability to pick superior funds. Funds with higher past inflows subsequently outperform their peers with money outflows. Karceski (2002) finds that speculative return-chasing investors across time and fund will motivate fund managers to take more risks. Funds may tilt their portfolios to high beta stocks which might reduce fund performance. Akbas et al. (2015) find that, on aggregate, relatively speculative hedge fund flows tend to be smarter than mutual fund flows. They show evidence that hedge fund flow can correct stock mispricing while mutual fund flows appear to exacerbate it. Agarwal, Green and Ren (2018) find that hedge fund investors rely more on exotic risk exposure than traditional risk exposure in their fund selection. Exotic risk can only be accessed via hedge funds rather than mutual funds. Motivated by statistics and prior literature, the behaviour of speculative investors and conservative investors will enhance our insights into the investment decision mechanism of mutual fund investors.

Chapter 4 What Drives Mutual Fund Flows? A Decomposed Approach to Risk and Non-risk Flow Determinants in China and the US

4.1 Introduction

There is a large body of literature examining the determinants of mutual fund flows.[6] However, most of the studies are only in the developed market. This study aims to compare what information drives fund investors' decision making between China and the US. The Chinese mutual fund market ranks first in the industry size among emerging markets in Asia.[7] It has experienced fast growth, the mutual fund's industry size of allocation funds and equity funds increased from 2.62 billion yuan in 2002 to 274.73 billion yuan in 2016 with the number of funds rising from 152 in 2006 to 1807 in 2016.

I contribute to the literature by testing the relative importance of the flow determinants proposed in the existing literature in the large emerging market of China compared with the US developed market. The capital asset pricing model (CAPM) has been found to be the dominant risk model in the US for directing mutual fund flows (Berk and Van Binsbergen, 2016), while this is puzzling given the inability of CAPM to predict cross-sectional stock returns (CAPM puzzle). The explanations for such a puzzle are still under debate. Barber, Huang and Odean (2016) suggest that sophisticated investors should make fund decisions using advanced benchmarks. With

[6]Risk factors, risk-adjusted alphas and fund characteristics have been found to affect fund flows. For example, risk-adjusted alphas and risk factors are investigated by Barber, Huang and Odean (2016), Berk and Van Binsbergen (2016), and Agawal, Green and Ren (2018); search costs and participation costs are studied by Sirri and Tufano (1998) and Huang, Wei and Yan (2007).
[7]According to a statistical report by the Asset Management Association of China (http://www.amac.org.cn/tjsj/qqgtjjsj/).

its different sophistication to the US market, studying risk models as fund flow determinants in the Chinese market would test existing findings 'out of (the US) sample.' If it is indeed the case that it is unsophisticated investors' ignorance of more advanced models that drives them to use the CAPM, I should find similar evidence in China as well.

Furthermore, my study is not limited to examining risk models. Non-risk factors have been documented as being important fund flow determinants. The literature shows that fund size has a negative impact on fund performance (Chen et al., 2004; Harvey and Liu, 2017); search costs and participation costs affect investor decisions (Sirri and Tufano, 1998; Huang, Wei and Yan, 2004); lagged fund flow is informative to predict better fund performance (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). In addition, investors may also consider active management skills. Studies find that active managers do have skills and add value for investors. Active skills in management include industry concentration index (Kacperczyk, Sialm and Zheng, 2005), fund diversification (Pollet and Wilson, 2008), return gaps (Kacperczyk, Sialm and Zheng, 2008), reliance on public information (Kacperczyk and Seru, 2007) and active shares (Ceremers and Petajisto, 2009). Therefore, to systematically study the decision mechanisms of mutual fund investors, my study covers both risk and non-risk factors.

Building on existing literature, I identify four groups of fund flow determinants. The first group of determinants is the risk loading of funds. In other words, it is the beta of risk factors calculated from risk models.[8] The existing literature finds empirical evidence that both market risk and non-market risk drive fund flows (Barber, Huang and Odean, 2016; Agarwal, Ren and Green, 2018). The second group is risk-adjusted performance. They are the alphas from the respective risk models in the first group. Existing literature shows that CAPM alpha dominates other risk-adjusted performance measures in determining fund flows (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016). However, if performance is not persistent, investors using past performance as an investment criterion might be irrational trend tracing.

The third group contains active investment skills, including fund diversification, industry concentration index, reliance on public information, active shares, fund-report attention and return gap. The existing literature shows that superior investment skills followed by better fund performance are found in funds with greater diversification, especially for small funds (Pollet and Wilson, 2008). More concentrated investing in a few industries predicts performance (Kacperczyk, Sialm and Zheng, 2005). Lower reliance on public information indicates higher skills (Kacperczyk and Seru, 2007). High active shares predict superior performance and indicate performance persistence (Cremers and Petajisto, 2009). Higher return gaps have predictive power for short-term fund performance (Kacperczyk, Sialm and Zheng, 2008). All of these suggest that there are non-risk factors that can be utilized to predict future fund performance. Therefore,

[8] I study five risk models: the capital asset pricing model (CAPM), the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF) in the China and US markets. For data availability in the US market, I also add the mispricing-factor model by Stambaugh and Yuan (2016). Hedge fund investors show relatively higher sensitivities to exotic risk rather than traditional risk obtained from hedge fund performance (Agarwal, Green and Ren, 2018).

these active investment skill measures may be a useful source of information for fund investors.

The final group of determinants contains essential fund characteristics such as fund size (total net assets), expense ratio, lagged flow, fund return volatility, etc. It has been documented that fund size erodes fund performance (Chen et al., 2004); funds with higher flows subsequently outperform their peers with lower flows (Zheng, 1999; Keswoni and Stolin, 2008); skilled managers charge higher fees (Sheng, Simutin and Zhang, 2017); fund flow is a U-shaped function of return volatility (Sirri and Tufano, 1998); lower participation costs indicate greater fund flows (Huang, Wei and Yan, 2004). As these factors are more straightforward for investors to understand and obtain, I include them in the fund characteristic group.

Empirically, for the Chinese market, I use the China stock market accounting research (CSMAR) mutual fund database via Wharton research data services (WRDS), including all equity funds and allocation funds (hold a large proportion of equity investments). For the US market, I obtain the fund characteristics data for US equity funds from the Morningstar Direct database. I have the following key findings.

First, confirming Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016), I show that CAPM alpha dominates other risk models in determining fund flows in the Chinese market. For the "no-model" series, the best one is market-adjusted fund return (ExMkt) which is equivalent to CAPM alpha assuming the fund has a unit beta. Utilizing the pairwise model test from Barber, Huang and Odean (2016), I find that CAPM alpha outperforms market-adjusted fund return in driving fund flows. This finding suggests that, in China, a large proportion of investors do use betas to assess fund performance.

Second, my results suggest that non-risk factors are more important in both the China and US markets than risk factors and risk-adjusted performance. I run fund flow determinant regressions using net flow as the dependent variable (Sirri and Tufano, 1998; Huang, Wei and Yan, 2007; Coval and Stafford, 2007; Barber, Huang and Odean, 2016; Franzoni and Schmalz, 2017). Independent variables are constructed at the beginning of the fund flow measurement period following Coval and Stafford (2007) and Barber, Huang and Odean (2016). To study the relative importance of each group of flow determinants, I employ an R-squared decomposition technique (Franzoni and Schmalz, 2017; Israeli, 2007; Devicienti, 2010; Sastre and Trannoy, 2002). I find that non-risk factors such as fund size and lagged flow play a dominant role in both the China and US markets. In China, fundamental characteristic factors provide explanatory power for fund flows ranging from 73.20% to 83.23%. Notably, lagged flow (41.95%) and fund size (21.51%) make a relatively higher contribution than CAPM alpha (10.71%). This finding suggests that the smart money effect and diminishing economies of scale play an important role in determining fund flows. As for active investment measures, they offer 6.32% to 7.56% of explanatory power, suggesting active investment factors are relevant but relatively unimportant determinants of fund flows in China. In the US, basic fund characteristics offer the highest explanatory power, ranging from 89.06% to 91.29%, for predicting flows across the whole sample period. Among the independent variables in the regression specification of CAPM, lagged fund flow has the highest explanatory power of 45.58%. In addition, fund size and Morningstar ratings are also the main concerns of US investors as they have explanatory power with decomposed R-squared of 14.85% and 15.18% respectively. CAPM alpha offers 10.33% of explanation of fund flows which is lower than non-risk factors.

Third, risk factors only have a limited role in explaining fund flow in both the China and US markets. They contribute from 1.96% (CAPM beta) to 17.67% (FF4 betas) in China and from 0.61% (CAPM beta) to 1.63% (FF5 betas) in the US of overall explanatory power in fund flow regressions. Additionally, past alphas from risk models provide more explanatory power than risk factors. For example, CAPM alpha offers the highest explanatory power among alphas of 10.71% in China and 10.33% in the US. This suggests "performance tracing" is one of the key characteristics of fund flows. Also, this finding is consistent with studies of the alpha-flow relationship in the US market where CAPM alpha is found to dominate the alphas of other more elaborate risk models, such as the Fama-French three-factor model or the Fama-French-Carhart model.

Fourth, fundamental fund characteristics show long-term predictive power in China, while their predictive power is relatively short-lived in the US. I conduct further tests that support fundamental fund characteristics being essential explanations of fund flows. I examine the explanatory power of these variables for longer-term fund flows (one to three years). In China, indeed, I observe that non-risk factors' ability to predict fund flows quickly increases once the period moves from a one-year to a three-year horizon. However, alpha and active measures see their explanatory power decrease as the forecast period lengthens. It is still the non-risk group that offers the highest explanatory power which is mainly attributable to fund size and fund flow. In contrast, I find the basic fund characteristics group does not significantly explain fund flows in the long term in the US market. This might be due to fund disclosure or the monthly frequency for US funds to report their assets, while in China funds report their assets on a quarterly basis. Therefore, it should be noted that the predictive power of alpha and active skill measures declines as the prediction period extends.

Fifth, I study the potential moderating effect of non-risk factors on alpha-flow sensitivity. I find that the interaction between the interaction group of alphas and fundamental fund characteristics contributes 14.58% in China and 13.07% in the US of explanatory power. In China, fund diversification and return gaps positively affect the power of CAPM alpha to drive fund flows, but past volatility shows a negative impact on it. In the US, lagged fund flows have a positive impact on the success of CAPM alpha outperforming other risk models, while fund size has a negative impact on it. It suggests the importance of these non-risk factors in moderating CAPM alpha's impact on fund flows.

Finally, I propose a new predictor, Smart-to-Dumb Ratio (SDR). It takes the decomposed R-squared of the fundamental fund characteristics group divided by the decomposed R-squared of the performance group to examine the performance implications of decomposed R-squared for the US market. I find that SDR significantly and positively predicts fund performance. A long-short portfolio based on SDR generates an annualized four-factor alpha ranging from 85.08 (t=3.94) basis points of an equal-weighted portfolio to 121.8 (t=2.33) basis points of a value-weighted portfolio, in a six-month holding period after formation. Consistent with Barber, Huang and

Odean (2016), sophisticated investors may utilize all factors whether priced or unpriced, to identify superior funds.

Overall, my results suggest that CAPM is the main risk model employed by mutual fund investors in China. Moreover, non-risk factors including fundamental fund characteristics are more important than risk betas and risk-adjusted alphas in both China and the US for determining fund flows. With this insight, Smart-to-Dumb Ratio (SDR) could be utilized to identify well-performing funds held by sophisticated investors. This evidence supports the findings by Barber, Huang and Odean (2016) that sophisticated investors use advanced benchmarks for fund selection. It also provides empirical evidence to support the explanations of the dominance of CAPM by Berk and Van Binsbergen (2016) in that non-risk factors could play an important role affecting the fund decisions of investors along with risk models.

This study first contributes to the growing literature on the determinants of fund flows. It sheds light on to what extent fund flows can be explained by both risk effects and non-risk effects (Berk and Van Binsbergen, 2016). It supports the power of fundamental fund characteristics to drive fund flows (Sirri and Tufano, 1998; Chen et al., 2004; Huang, Wei and Yan, 2007; Nanda, Wang and Zheng, 2004; Keswani and Stolin, 2008). It also provides empirical evidence from the mutual fund industry of the largest emerging market, China. This unique and newly developing market has investors with different educational backgrounds and investment philosophies from those of US investors, and I find that non-risk factors have substantial weight in their consideration when choosing funds in the long term.

Second, it provides new evidence for the relative importance of fund flow determinants. As literature develops, new determinants are identified. However, the importance of these new determinants can only be assessed in the context of existing ones. Existing determinants are often featured in regressions as control variables. However, the comparison between determinants is implicit. The importance of a new determinant may be overemphasised, while an explicit measure without too many data requirements would be more accessible to investors (Amihud and Goyenko, 2013). Also, sophisticated investors should utilize all factors with advanced benchmarks in their decision-making (Barber, Huang and Odean, 2016; Agarwal, Green and Ren, 2018). I highlight the importance of such a unified study and provide a framework for classifying the relative importance of determinants with a Shapely-Owen R-squared decomposition technique.

Third, I provide evidence that flow determinants have long-term (one year to three years) predictive power for fund flows in China, but their predictive power is short-lived (within one year) in the US. Fund size, past volatility and fund family size are key factors that have increasing explanatory power, affecting long-term fund flows. In contrast, lagged fund flow, CAPM alpha and active measures show decreasing explanatory powers. In China, I also provide evidence of active investment factors driving flows which reinforces existing findings in the literature that only concentrates on the developed market.[9]

[9] Empirically, Kacperczyk, Sialm and Zheng (2005) find that funds with concentrated investments in a few industries have better performance; Kacperczyk and Seru (2007) find that skilled managers who rely less on analysts' recommendations can outperform others; Pollet and Wilson (2008) show that diversified funds, especially for small-cap funds, outperform others; Cremers and Petajisto (2009) find that higher active shares predict superior and persistent

Fourth, I contribute to the literature in identifying well-performing funds, which is related to the literature on fund performance predictions (Cemers and Petajisto, 2009; Kacpczyk, Sialm and Zheng, 2005; Kacpczyk and Seru, 2007). From the perspective of decomposed R-squared, the fund flows of sophisticated investors are predictive of future performance. It applies a new method to identify performance predictors from an investor perspective, and it provides an empirical metric to measure smart money. Utilizing Smart-to-Dumb Ratio (SDR), investors can recognize funds with superior fund performance.

The remainder of this study is organized as follows. I review the literature and describe proxies for risk factors and non-risk factors in Section 4.2. I propose hypotheses in Section 4.3 and describe the sample and methodology in Section 4.4. I present analyses of flow determinants in Section 4.5, confirm the robustness of results in Section 4.6, examine the performance implications of decomposed R-squared in Section 4.7 and conclude in Section 4.8.

4.2 Literature Review of Flow Determinants

Extensive literature explores the determinants of mutual fund flows in the earlier stage. Scholars find that investors are sensitive to fund performance (Ippolito,1992; Chevalier and Ellison, 1997; Berk and Green, 2004); investors should employ risk models (Berk and Van Binsbergen, 2016) and utilize all factors to assess fund performance (Barber, Huang and Odean, 2016); active investment skills exist and predict performance

performance; Jenkinson, Jones and Martinez (2016) further confirm that soft investment factors, such as clear investment decisions, capable professionals and consistent investment strategies mainly determine analysts' recommendations, and mutual fund flows are significantly affected by analysts' recommendations. My findings are consistent with these papers, and I argue that investors are also aware of active investment factors along with risk factors.

(Kacpercyzk, Sialm and Zheng, 2007; Cremers and Petajisto, 2009); fundamental fund characteristics including search costs, participation costs, fund fees and lagged flows significantly affect the decisions of investors in fund-picking (Sirri and Tufano, 1998; Huang, Wei and Yan, 2007; Barber, Odean, Zheng, 2003; Gruber, 1996; Zheng, 1999; Kewani and Stolin, 2008). Consistent with these works providing evidence that flows are affected by multiple factors, I define four groups of essential flow determinants: risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics.

For risk betas, the literature documents that the risk exposure of mutual funds is considered by investors. Fund managers manage to outperform by investing in higher beta stocks to attract investors (Karceski, 2002; Baker, Bradley and Wurgler, 2011). Low beta stocks significantly outperform higher beta ones (Frazzini and Pedersen, 2014). The abnormal return of beta strategies occurs relatively quickly when arbitrage activity is greater (Huang, Lou and Polk, 2016). Moreover, Christoffersen and Simutin (2017) also find that high beta strategies can improve fund returns relative to their benchmarks which attract money inflows. Bogth and Simutin (2018) find that fund managers can utilize the implicit leverage embedded in high-beta stocks to handle leverage constraints. Funds with higher-beta exposure outperform their peer funds with low beta by 5% annually. Following these studies, I assume that investors should account for risk loadings on fund returns by fund managers in their investments. I explore whether investors tend to consider risk betas from the CAPM, the Fama-French three-factor, the Fama-French-Carhart, the Fama-French five-factor and the Q-factor model.

For risk-adjusted alpha, Berk and van Binsbergen (2016) utilize mutual fund flows to test the performance of different risk models. They find that CAPM alpha best captures the investment preferences of mutual fund investors. Baber, Huang and Odean (2016) also find that CAPM alpha outperforms other risk models in directing the capital flows of mutual fund investors. They find that investors tend to employ alphas rather than betas to assess funds. They argue that sophisticated investors will take advantage of all priced or unpriced factors to pick funds. Moreover, Agarwal, Green and Ren (2016) confirm that CAPM alpha also best explains hedge fund flows and outperforms other multiple risk models. They document that investors pool factor-related returns together with alpha when assessing fund performance. Unlike these papers that explore model performance in developed markets, I extend model performance tests to the mutual fund industry of the largest emerging market, China.

My study is also connected to the literature studying active management skills. It has been documented that fund managers who invest in concentrated industries tend to outperform others. Funds invest more in growth and small stocks with a distinct investment style since fund managers have experience and skills relevant to specific industries (Kacperczyk, Sialm and Zheng, 2005). The return gap is the difference between fund returns and returns calculated from a fund portfolio. Superior funds may have greater return gaps which reflect managers' unobserved ability in market timing or the ability to manage hidden costs relating to trading, brokerage and externalities. (Kacperczyk, Sialm and Zheng, 2008). In addition, skilled managers change their portfolio allocations less in response to publicly available analysts' recommendations. Reliance on public information (RPI) reversely predicts fund performance (Kacperczyk and Seru, 2007). Funds with more diversified investments tend to outperform their peers. Especially, funds of small size benefit more from fund diversification (Pollet and Wilson, 2008). In addition, funds with more active shares that have a greater deviation in stock weight from the stock weight in funds' benchmark indices can outperform their peers. (Cremers and Petajisto, 2009); well-advertised funds appear to attract more money inflows (Jain and Wu, 2000); advertised funds can reduce the search costs of investors and induce higher flows than their unadvertised peers (Srri and Tufano, 1998); fund managers with excellent skills in stock picking and investment activity trade less on common risk factors such as size, value, and momentum. This is measured by the R-squared that regresses fund returns on common risk factors. A lower R-squared predicts better fund performance(Amihud and Goyenko, 2013). Based on the literature, I adopt fund diversification, industry concentration, fund-report attention, active share and return gap as non-risk factors.

For fundamental fund characteristics, I identify three main strands of literature studying fund size, lagged fund flows and Morningstar rating. Scale-decreasing returns have been well documented that fund size erodes fund performance (Chen et al., 2004), which is attributable to portfolio liquidity and hierarchy costs in organizational diseconomies. Also, Pollet and Wilson (2008) find that investment opportunities do not expand with fund size growth, which explains scale-decreasing returns. In addition, Pástor and Stambaugh (2012) also confirm that management skills decrease as industry size grows. Furthermore, scale-decreasing returns can also be explained by liquidity constraints, especially for funds investing in small and domestic US stocks (Ferreira et al. 2013). Also, Berk and Van Binsbergen (2015) address that the skill of fund managers can be measured by the value they add (size), rather than gross alpha of the return level. Yin (2016) find that fund size also negatively affects performance in hedge funds, and hedge fund managers have incentives to increase their assets at the expense of fund performance. Following the literature above, I hypothesize that investors are aware of size in their fund picking. I adopt fund size as the main non-risk factor in my analysis.

The smart money effect has been well documented by earlier studies. As for fund lagged flows, Gruber (1996) finds that investors are able to find performance predictors to pick superior funds. The strategy of investing in funds with higher net cash flows subsequently generates positive and significant risk-adjusted alphas. Zheng (1999) also finds that funds receiving large money inflow subsequently outperform funds suffering money outflows. She documents that the smart-money effect is short-lived and the effect is stronger for small funds. Keswani and Stolin (2008) find that the smart money effect also exists in the UK market, and it is caused by buying behaviour, rather than selling, of both institutional investors and retail investors. Investors should know that past fund flows are informative to predict future fund performance. Following these papers, I take lagged fund flow as the main non-risk factor.

For Morningstar ratings, Blake and Morey (2000) find that investors can utilize low Morningstar ratings to identify poorly performing funds, but they cannot pick superior funds using high Morningstar ratings. Guercio and Tkac (2008) find that investors are sensitive to changes in Morningstar ratings rather than fund performance. They punish funds when they drop to 3 stars (or below one-third of rated funds) and reward them disproportionately and positively when the ratings rise back to 5 stars. Armstrong, Genc and Verbeek (2017) find that higher Morningstar analyst ratings also significantly induce money inflows. Investors can benefit from gold-rated funds by 120 basis points annually compared to low rated peers. Nanda, Wang and Zheng (2004) find that higher rated funds have spillover effects in a fund family. Star-rated fund attracts alternative money flows for the other funds within the same fund family. As studies show that Morningstar ratings significantly affect fund flows, I take them as one of the main non-risk factors.

Moreover, a small but growing strand of literature studies other fund characteristics that fund fees, fund family size, fund age, manager tenure, return volatility and fund turnover also affect the fund decisions of investors. It documents that investors are sensitive to marketing expenses (12b-1 fees) within operating costs, and poorly performing funds charge higher fees by targeting performance-insensitive investors while well-performing funds charge low fees due to competition and performance-sensitive investors (Barber, Odean and Zheng, 2005; Gil-Bazo and Ruiz-verdu, 2009). Large fund families have lower search costs, which attracts more investor inflows, and fund family size positively predicts fund performance (Sirri and Tufano, 1998; Bhojraj, Cho and Yehuda, 2011). Young funds tend to outperform their old peers, and a longer manager tenure indicates better performance (Pástor, Stambaugh and Taylor, 2015); the sensitivity of flows to returns decreases in funds with high volatility (Huang, Wei and Yan, 2004). Fund skills are associated with the trading frequency of fund managers. Funds with higher active share but trades infrequently with lower fund turnover tend to outperform others (Cremers and Pareek, 2016). Based on the literature above, I include fund fee, fund family size, fund age, manager tenure, return volatility and fund turnover in non-risk factors.

4.3 Hypotheses Development

I develop three main hypotheses to investigate the role of risk models and non-risk factors affecting investors' fund allocations and how investors' concerns about risks and non-risk factors can be utilized as predictors for fund performance. Given the dominance of CAPM in the fund decision-making of mutual fund investors (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016; Agarwal, Green and Ren, 2018), my first hypothesis focuses on the role of CAPM in the fund decisions of Chinese investors.

Hypothesis 1 (H1): The Capital Asset Pricing Model (CAPM) dominates other risk models in the fund decisions of Chinese mutual fund investors.

Berk and Van Binsbergen (2016) argue that non-risk effect may explain why CAPM outperforms other risk models in modelling fund flows in the US. They document that risk-adjusted alphas and risk betas calculated from returns are only one perspective of the information supply to investors. Non-risk factors may also be a relatively valuable perspective for investors to select funds. Additionally, Barber, Huang and Odean (2016) argue that sophisticated investors may consider all factors whether priced or unpriced, in fund picking. With this logic, I link flow determinant analysis to the literature studying non-risk factors.

I find that the literature shows evidence that fund size erodes fund performance (Chen et al., 2005; Pollet and Wilson, 2008); reducing search costs (Sirri and Tufano, 1998) and participation costs (Huang, Wei and Yan, 2007) can induce money inflows; funds receiving higher capital inflow subsequently outperform their peer funds, which experience fund outflows (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). Also, concentrated investments exhibit better performance (Kacperczyk, Sialm and Zheng, 2005); active share predicts superior performance (Cremers and Peajisto, 2009); skilled fund managers rely less on public information (Kacperczyk and Seru, 2007). So, sophisticated investors may be aware of these non-risk factors in their fund selection. Then, non-risk factors may have exerted explanatory power in fund flow decisions. Moreover, the different sophistication between the US and China can give us more insights into the decision mechanism of mutual fund investors. I expect that non-risk factors can explain future fund flows along with risk factors. Thus, I have my second hypothesis:

Hypothesis 2 (H2): Non-risk factors outperform risk factors and risk-adjusted performance in explaining future capital flows.

In addition, risk-adjusted fund performance and risk betas may be more volatile than fundamental fund characteristics in the longer term. Regarding the investment horizon, there is a strand of literature that finds that performance persistence is often short-lived. Carhart (1997) finds that the performance persistence of mutual funds is explained by the one-year momentum effect and it disappears after one year, which does not support superior management skills. Bollen and Busse (2005) find that mutual fund performance is not persistent in the long term and excellent management is short-lived. Berk and Green (2004) document that performance is not persistent in their model. They show that performance-chasing investors make full advantage of past fund information. These investors increase flows to funds at the point which expected excess returns going forward are competitive. This process indicates that positive excess returns are not predictable, so superior managerial skills are also not predictable.

As performance persistence varies with the period (Brown and Goetzmann, 1995) or is short-lived (Bollen and Busse, 2005), I expect that the influence of risk factor on fund flow will be relatively shorter-lived than fundamental characteristics. Hence, Extended Hypothesis 2 is developed as follows:

Extended Hypothesis 2: Non-risk factors outperform risk-factors and risk-adjusted performance in the longer term in attracting money flows.

An R-squared decomposition technique allows us to find a measurable proxy to understand the relative importance of determinants in the decision mechanism of mutual fund investors. As decomposed R-squared implies why investors purchase or withdraw their money from funds, I assume that funds held more by fundamental characteristics-driven investors and less by performance-chasing investors will have better performance. This is motivated by the literature finding that the superior performance of mutual funds is short-lived and its persistence is time-varying (Carhart, 1997; Bollen and Busse, 2005; Berk and Green, 2004). Moreover, fundamental fund characteristics including fund size, lagged flows and fund fees are widely explored and found to affect fund performance significantly (Chen et al., 2004; Huang, Wei and Yan, 2007; Barber, Odean and Zheng, 2005). Also, fundamental fund characteristics will be more explicit and easier to understand by most mutual fund investors, compared to other measures. Thus, Hypothesis 3 is developed as follows:

Hypothesis 3 (H3): Funds held by investors with greater concerns over non-risk factors (fundamental fund characteristics) and less reliance on past performance (risk-adjusted alphas) tend to have better performance than their peers.

4.4 Sample and Measurements

4.4.1 Mutual Fund Sample

4.4.1.1 China Sample

The primary source of Chinese fund data is the CSMAR mutual fund database. I use the Morningstar categories and select equity funds (45), sector equity health funds (5), sector equity technology and communications funds (1), aggressive allocation funds (459) and moderate allocation funds (55) with their assets mainly investing in equities. I remove all index funds, bond funds and money funds and examine all actively-managed equity funds and allocation funds (or labeled as mixed funds in China) with larger than 50% equity holdings and at least 24-month history, from 2004 to 2016, which leaves 565 funds in my sample.[10] I take all available fund data from the start of this Chinese mutual fund database. According to a new act from the China Securities Regulatory Commission, an equity fund must raise its stock holdings from at least 60% to at least 80% since 8 August 2014. If the position of a fund on either stocks or bonds is less than 80%, it shall be called an allocation fund.[11] To make the sample comparable to other research and avoid bias from extreme values, I follow Franzoni and Schmalz (2017) and Elton, Gruber and Blake (2001) and winsorize fund flow, total expense ratio, return volatility, return gap and reliance on public information at the 1st and 99th percentiles. I extract main fund characteristics, quarterly performance data, semi-annual financial information and semi-annual fund holdings data within a 13-year span of

[10] The Morningstar categories of aggressive allocation, moderate allocation and allocation funds are included in our allocation fund sample. They have more than a 50% of equity holding in their portfolios.

[11] The previous criterion for equity funds' equity holdings is at least 60 % invested in the stock market until 8 August 2014. A number of equity funds changed their name to allocation funds after the implementation of the act. The official document can be found at：
http://www.csrc.gov.cn/zjhpublic/G00306201/201407/t20140711_257656.htm

2004-2016.[12] I merge fund characteristics with stock characteristics based on funds' specific holdings. The stock data source is downloaded from the CSMAR stock database. Also, analysts' coverage data for each stock are extracted from the China-listed firm's research database of analyst series.

Table 4-1 Descriptive Statistics for the Chinese Mutual Fund Market

This table presents summary statistics for the China sample from 2004 to 2016. In Panel A, it reports summary statistics of all risk-adjusted alphas, betas, active investment factors and fundamental fund characteristics. Risk-adjusted alphas and risk betas are calculated from the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF) with 24-month rolling window regressions. Active investment factors include fund diversification, industry concentration index (ICI), reliance on public information (RPI), active share, fund-report attention and return gap. Fundamental fund characteristics include fund size (in millions of yuan), fund family size (in millions of yuan), fund ages, operating ratio, lagged fund flow and prior 12-month return volatility. Pearson correlations are reported in Panel B.

Panel A:

Variables	**N**	**Mean**	**SD**	**Min**	**P25**	**Median**	**P75**	**Max**
Risk-adjusted alphas								
CAPM alpha	14389	0.22%	0.88%	-3.71%	-0.26%	0.20%	0.69%	7.09%
FF3 alpha	14389	-0.07%	1.04%	-5.45%	-0.62%	-0.05%	0.49%	11.67%
FF4 alpha	14389	0.04%	1.08%	-7.17%	-0.48%	0.03%	0.54%	12.28%
FF5 alpha	14389	-0.05%	1.09%	-6.21%	-0.63%	-0.02%	0.53%	11.78%
QF alpha	14389	-0.78%	1.37%	-9.17%	-1.55%	-0.68%	0.03%	9.83%
Risk betas								
Beta MKT CAPM	14389	0.78	0.22	-0.23	0.66	0.79	0.91	1.76
Beta MKT FF3	14389	0.73	0.21	-0.53	0.62	0.74	0.86	2.19
Beta SMB FF3	14389	0.11	0.34	-1.91	-0.10	0.07	0.29	1.51
Beta HML FF3	14389	-0.19	0.47	-2.66	-0.44	-0.18	0.05	2.04
Beta MKT FF4	14389	0.77	0.21	-0.96	0.66	0.78	0.89	2.21
Beta SMB FF4	14389	0.06	0.32	-2.23	-0.11	0.05	0.23	1.74
Beta HML FF4	14389	-0.25	0.45	-4.42	-0.47	-0.19	0.01	2.25

[12] The first open-end mutual fund in China is the "Huaan Innovation" fund which started in September 2001.

Table 4-1 (continued)

Beta UMD FF4	14389	0.23	0.37	-2.11	0.01	0.24	0.45	2.19
Beta MKT FF5	14389	0.77	0.23	-0.92	0.66	0.78	0.91	2.28
Beta SMB FF5	14389	0.21	0.43	-2.80	-0.05	0.18	0.45	2.29
Beta HML FF5	14389	-0.19	0.47	-4.32	-0.45	-0.19	0.05	2.87
Beta CMA FF5	14389	-0.17	0.69	-4.07	-0.49	-0.10	0.20	4.07
Beta RMW FF5	14389	0.22	0.68	-3.76	-0.11	0.22	0.59	4.31
Beta MKT QF	14389	0.79	0.21	-0.61	0.69	0.81	0.92	2.51
Beta SMB QF	14389	0.31	0.40	-2.17	0.06	0.29	0.55	1.88
Beta I/A QF	14389	-0.23	0.43	-3.07	-0.47	-0.18	0.00	2.29
Beta ROE QF	14389	0.22	0.46	-2.61	-0.01	0.23	0.47	3.47
Active investment factors								
Diversification	15079	3.92	0.60	0.00	3.56	3.89	4.25	6.85
Industry concentration index	10720	0.05	0.04	0.00	0.02	0.03	0.05	0.58
Reliance on public information	9535	0.17	0.24	-0.15	0.01	0.07	0.24	0.97
Active share	9502	0.12	0.09	0.00	0.05	0.10	0.18	0.56
Fund-report attention	13053	3.50	0.65	-4.77	3.19	3.66	3.96	4.54
Return gap	10272	-0.08	0.15	-0.71	-0.15	-0.05	0.02	0.25
Fundamental characteristics								
Fund return	15447	1.46%	9.86%	-80.69%	-4.05%	0.95%	5.69%	98.10%
Fund size	15660	2851.51	4094.86	2.80	354.21	1340.31	3602.21	48174.03
Fund size (log)	15660	20.81	1.56	14.85	19.69	21.02	22.00	24.60
Flow	14774	-2.80%	28.97%	-62.63%	-11.48%	-4.03%	-0.69%	293.47%
Total operating cost	15156	2.34%	1.32%	0.51%	1.32%	2.05%	2.94%	8.36%
Volatility	15323	7.48%	3.52%	0.97%	4.90%	6.53%	9.56%	19.15%
Age (quarter)	15671	17.52	12.43	0.00	7.00	15.00	26.00	61.00
Age (quarter) log	15671	2.52	0.96	0.00	1.95	2.71	3.26	4.11
Family size	15660	1873.28	1549.66	8.63	760.35	1413.84	2608.14	11861.50
Family size (log)	15660	20.97	0.99	15.97	20.45	21.07	21.68	23.20

Table 4-1 (continued)

Panel B:

Correlation	Fund return	Fund size	Flow	Total expense ratio	Volatility	Age (quarter)	Family size	CAPM alpha	CAPM beta	Diver.	ICI	RPI	Active share	Fund-report attention	Return gap
Fund return	1.00	0.01	0.04	0.02	0.03	-0.02	0.01	0.14	-0.04	0.03	0.01	0.00	-0.01	-0.09	-0.01
Fund size	0.01	1.00	0.04	-0.14	0.02	0.05	0.59	0.12	-0.02	0.36	-0.03	-0.12	0.15	0.12	0.01
Flow	0.04	0.04	1.00	0.00	0.08	-0.03	0.04	0.12	0.05	0.02	0.06	0.03	0.01	0.00	0.03
Total expense ratio	0.02	-0.14	0.00	1.00	0.10	-0.18	-0.08	-0.03	0.04	-0.09	0.02	0.05	-0.11	-0.07	0.08
Volatility	0.03	0.02	0.08	0.10	1.00	0.09	-0.03	-0.14	0.62	0.05	0.14	0.09	-0.11	-0.15	-0.06
Age (quarter)	-0.02	0.05	-0.03	-0.18	0.09	1.00	0.01	-0.18	0.19	0.10	-0.07	-0.13	-0.12	0.10	-0.01
Family size	0.01	0.59	0.04	-0.08	-0.03	0.01	1.00	0.11	-0.05	0.21	0.00	-0.08	0.04	0.14	0.02
CAPM alpha	0.14	0.12	0.12	-0.03	-0.14	-0.18	0.11	1.00	-0.23	0.04	0.01	0.02	0.03	-0.03	0.13
CAPM beta	-0.04	-0.02	0.05	0.04	0.62	0.19	-0.05	-0.23	1.00	0.13	0.09	0.00	-0.05	0.13	-0.01
Diversification	0.03	0.36	0.02	-0.09	0.05	0.10	0.21	0.04	0.13	1.00	-0.10	-0.24	0.11	0.21	0.06
Industry concentration index	0.01	-0.03	0.06	0.02	0.14	-0.07	0.00	0.01	0.09	-0.10	1.00	0.03	0.01	-0.02	0.05
Reliance on public information	0.00	-0.12	0.03	0.05	0.09	-0.13	-0.08	0.02	0.00	-0.24	0.03	1.00	-0.11	-0.22	-0.08
Active share	-0.01	0.15	0.01	-0.11	-0.11	-0.12	0.04	0.03	-0.05	0.11	0.01	-0.11	1.00	0.31	0.05
Fund-report attention	-0.09	0.12	0.00	-0.07	-0.15	0.10	0.14	-0.03	0.13	0.21	-0.02	-0.22	0.31	1.00	0.12
Return gap	-0.01	0.01	0.03	0.08	-0.06	-0.01	0.02	0.13	-0.01	0.06	0.05	-0.08	0.05	0.12	1.00

In Table 4-1 Panel A, I present summary statistics for risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics. On average, the sample funds have a positive four-factor alpha of 0.04% with a median of 0.03%. CAPM beta has a mean of 0.78 with a median of 0.79. For fund size, on average, the sample funds have the mean value of 2851.51 million yuan. It ranges from 2.8 to 48174.03 million yuan. For fund flows, it shows an average negative flow of -2.8% with a median -4.03% which indicates that the market experiences an outflow on the aggregate level.

4.4.1.2 US Sample

I obtain primary mutual fund data from the Morningstar Direct database, which includes 1946 equity funds and covers 2004-2016. Following Kacperczyk, Sialm and Zheng (2005), I focus on actively managed equity funds and remove bond, money market, international, sector and index funds. To avoid potential bias from small funds, I consider all US domestic equity funds that reach $10 million (Barber, Huang and Odean, 2016). I start the monthly sample from 2004 and require at least five-year monthly data to compute risk-adjusted performance. For funds with multiple share classes, I follow Simutin (2013) and Barber, Huang and Odean (2016) and aggregate fund characteristics into a single fund. For fund size, I take the sum of net assets across different share classes. For fund net return, gross returns, total expense ratio and turnover, I take the value-weighted average of them across share classes. I take the inception date of the oldest share class to calculate fund age.

In robustness tests, I identify institutional funds if their name contains "Institution." Following Sun (2014), I recognize a broker-sold fund if a fund charges a 12b-1 fee greater than

0.25%, or it has a front-end load or a back-end load. I identify a co-managed fund if a fund has two managers or more. Based on Chiu and Kini (2014) and Barber, Huang and Odean (2016), I adopt aggregate mutual fund flow as the proxy of market sentiment. I identify a high sentiment period if the sentiment is larger than the median level across my sample. For fund age, fund size, family size, fund turnover, expense ratio and return volatility, I set a dummy variable equal to one if it is larger than its cross-sectional median.

Table 4-2 Descriptive Statistics for the US Mutual Fund Market

This table reports summary statistics for fundamental fund characteristics, Morningstar ratings, fund risk-adjusted alpha, risk betas and decomposed R-squared based on the determinants of fund flows from 2004 to 2016. It includes monthly fund returns, fund size (in millions of dollars), family size (in millions of dollars), flow volatility, flow, category flow, expense ratio, turnover, age (months), Morningstar 3-year ratings, Morningstar 5-year ratings, prior 12-month fund return volatility and prior 12-month fund flow volatility. Risk-adjusted alphas and betas are calculated from 60-month rolling windows with monthly data using the CAPM, the Fama-French model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5), the Q-factor model (QF) from Hou, Xue and Zhang (2014) and the mispricing-factor model (MF) from Stambaugh and Yuan (2016). I report summary statistics in Panel A. Pearson correlations are represented in Panel B.

Panel A:

Variables	**N**	**Mean**	**SD**	**Min**	**P25**	**Median**	**P75**	**Max**
Decomposed R-squareds								
SDR	171583	3.00	2.44	0.35	1.63	2.32	3.53	62.26
Fund characteristic R-squared	171583	0.51	0.13	0.16	0.41	0.50	0.59	0.96
Morningstar rating R-squared	171583	0.07	0.06	0.00	0.02	0.05	0.10	0.63
Traditional risk-adjusted performance R-squared	171583	0.21	0.09	0.01	0.15	0.20	0.26	0.66
Exotic risk-adjusted performance R-squared	171583	0.21	0.07	0.02	0.16	0.21	0.26	0.68

Table 4-2 (continued)

Risk-adjusted alphas								
CAPM alpha	171583	-0.08%	1.78%	-18.58%	-1.00%	-0.10%	0.80%	23.15%
FF3 alpha	171583	-0.11%	1.45%	-17.97%	-0.86%	-0.10%	0.65%	18.29%
FF4 alpha	171583	-0.10%	1.46%	-17.68%	-0.84%	-0.09%	0.65%	22.26%
FF5 alpha	171583	-0.09%	1.45%	-18.92%	-0.84%	-0.09%	0.66%	20.48%
QF alpha	171583	-0.26%	1.61%	-18.80%	-1.08%	-0.21%	0.60%	23.26%
MF alpha	171583	-0.07%	1.45%	-17.02%	-0.85%	-0.07%	0.70%	24.94%
Risk betas								
Beta MKT CAPM	171583	1.06	0.17	0.28	0.96	1.05	1.16	2.57
Beta MKT FF3	171583	1.02	0.13	0.23	0.95	1.02	1.09	2.06
Beta SMB FF3	171583	0.25	0.35	-0.62	-0.05	0.17	0.55	1.55
Beta HML FF3	171583	-0.02	0.28	-1.22	-0.22	-0.01	0.17	1.86
Beta MKT FF4	171583	1.02	0.13	0.23	0.95	1.02	1.09	2.05
Beta SMB FF4	171583	0.25	0.35	-0.65	-0.05	0.16	0.54	1.56
Beta HML FF4	171583	-0.02	0.27	-1.15	-0.22	-0.02	0.16	1.79
Beta UMD FF4	171583	0.00	0.11	-1.12	-0.06	0.00	0.05	0.77
Beta MKT FF5	171583	1.01	0.11	0.22	0.95	1.01	1.07	1.80
Beta SMB FF5	171583	0.25	0.35	-0.61	-0.05	0.16	0.56	1.54
Beta HML FF5	171583	-0.02	0.25	-1.15	-0.21	-0.02	0.15	1.68
Beta CMA FF5	171583	-0.12	0.23	-1.93	-0.26	-0.10	0.03	1.02
Beta RMW FF5	171583	-0.03	0.20	-1.69	-0.13	-0.01	0.10	1.01
Beta MKT QF	171583	1.01	0.14	0.25	0.95	1.02	1.08	2.57
Beta SMB QF	171583	0.21	0.29	-0.62	-0.03	0.14	0.44	1.57
Beta I/A QF	171583	-0.08	0.23	-1.55	-0.22	-0.06	0.07	1.22
Beta ROE QF	171583	0.04	0.18	-1.65	-0.07	0.04	0.14	1.19
Beta MKT MF	171583	0.99	0.12	0.22	0.93	1.00	1.06	1.94
Beta SIZE MF	171583	0.24	0.36	-0.64	-0.06	0.13	0.54	1.51
Beta MGMT MF	171583	-0.13	0.25	-1.36	-0.29	-0.12	0.03	1.03
Beta PERF MF	171583	0.00	0.13	-1.24	-0.08	0.01	0.09	0.74
Fundamental characteristics								
Fund net return	171583	0.71%	4.82%	-32.93%	-1.77%	1.14%	3.64%	31.68%
Fund gross return	171583	0.81%	4.82%	-32.89%	-1.68%	1.24%	3.74%	31.85%
Market excess return	171583	-0.06%	1.81%	-18.16%	-0.97%	-0.07%	0.84%	24.24%
Risk-free excess return	171583	0.64%	4.83%	-33.01%	-1.85%	1.04%	3.56%	31.67%
Flow	171583	-0.42%	7.99%	-88.59%	-1.55%	-0.65%	0.28%	937.87%
Category flow	171583	2.47	4.38	-8.11	-0.17	1.59	4.47	43.69
Fund size	171583	2031.54	6740.23	10.00	142.53	485.52	1506.79	202305.76
Fund size (log)	171583	20.00	1.67	16.12	18.78	20.00	21.13	26.03
Family size	171583	41904.78	94927.49	10.11	1894.86	11980.95	33135.52	589003.89
Family size (log)	171583	22.74	2.24	16.13	21.36	23.21	24.22	27.10

Table 4-2 (continued)

Age (month)	171583	232.02	151.56	90.00	140.00	188.00	260.00	1109.00
Expense ratio	171583	1.19%	0.35%	0.27%	0.96%	1.17%	1.39%	2.66%
Load dummy	171583	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Turnover	171583	0.69	0.53	0.02	0.31	0.56	0.91	3.43
Return volatility	171583	0.04	0.02	0.01	0.03	0.04	0.05	0.18
Flow volatility	171583	0.03	0.04	0.00	0.01	0.01	0.03	0.49
Morningstar ratings								
MS overall rating	171583	3.06	0.96	1.00	2.21	3.00	3.99	5.00
MS 3-year rating	171583	2.98	1.08	1.00	2.00	3.00	4.00	5.00
MS 5-year rating	171442	3.00	1.09	1.00	2.00	3.00	4.00	5.00
MS 10-year rating	148074	3.05	1.11	1.00	2.00	3.00	4.00	5.00

Table 4-2 (continued)

Panel B:

Correlation	Fund return	Fund gross return	Flow	Category flow	Fund size	Family size	Age (month)	Expense ratio	Load dummy	Turnover	Return volatility	Flow volatility	MS overall rating	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	QF alpha	MF alpha	Beta MKT CAPM
Fund return	1.00	1.00	0.02	0.12	0.01	0.01	0.00	-0.01	-0.01	-0.02	0.09	0.01	0.03	0.32	0.26	0.27	0.25	0.26	0.26	-0.02
Fund gross Return	1.00	1.00	0.02	0.12	0.01	0.01	0.00	0.00	-0.01	-0.02	0.09	0.01	0.03	0.32	0.26	0.27	0.25	0.26	0.26	-0.02
Flow	0.02	0.02	1.00	0.04	0.01	0.01	-0.01	-0.02	0.00	-0.01	-0.01	0.03	0.12	0.01	0.01	0.01	0.01	0.01	0.01	-0.04
Category flow	0.12	0.12	0.04	1.00	0.03	0.01	0.01	0.00	0.03	0.01	-0.19	-0.01	-0.01	0.02	0.01	0.01	0.02	0.03	0.01	-0.16
Fund size	0.01	0.01	0.01	0.03	1.00	0.38	0.23	-0.25	-0.02	-0.12	-0.08	-0.09	0.16	0.01	0.01	0.01	0.01	0.03	0.01	-0.09
Family size	0.01	0.01	0.01	0.01	0.38	1.00	0.11	-0.29	-0.06	0.02	-0.06	-0.06	0.07	0.00	0.01	0.00	0.01	0.02	0.01	0.03
Age (month)	0.00	0.00	-0.01	0.01	0.23	0.11	1.00	-0.17	0.05	-0.06	-0.07	-0.11	-0.02	0.00	0.00	0.00	0.00	0.03	0.00	-0.08
Expense ratio	-0.01	0.00	-0.02	0.00	-0.25	-0.29	-0.17	1.00	0.22	0.18	0.14	0.05	-0.27	0.00	-0.02	-0.01	-0.01	-0.05	-0.01	0.15
Load dummy	-0.01	-0.01	0.00	0.03	-0.02	-0.06	0.05	0.22	1.00	0.09	0.00	0.01	-0.10	0.00	0.00	0.00	0.00	0.01	0.00	-0.02
Turnover	-0.02	-0.02	-0.01	0.01	-0.12	0.02	-0.06	0.18	0.09	1.00	0.15	0.09	-0.17	0.00	-0.02	-0.02	-0.01	-0.03	-0.03	0.17
Return volatility	0.09	0.09	-0.01	-0.19	-0.08	-0.06	-0.07	0.14	0.00	0.15	1.00	0.05	-0.08	0.01	-0.02	0.01	0.02	-0.03	-0.01	0.35
Flow volatility	0.01	0.01	0.03	-0.01	-0.09	-0.06	-0.11	0.05	0.01	0.09	0.05	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
MS overall rating	0.03	0.03	0.12	-0.01	0.16	0.07	-0.02	-0.27	-0.10	-0.17	-0.08	0.00	1.00	0.09	0.11	0.10	0.10	0.09	0.09	-0.25
CAPM alpha	0.32	0.32	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.09	1.00	0.74	0.68	0.70	0.76	0.74	-0.03
FF3 alpha	0.26	0.26	0.01	0.01	0.01	0.01	0.00	-0.02	0.00	-0.02	-0.02	0.00	0.11	0.74	1.00	0.92	0.94	0.78	0.83	-0.04
FF4 alpha	0.27	0.27	0.01	0.01	0.01	0.00	0.00	-0.01	0.00	-0.02	0.01	0.00	0.10	0.68	0.92	1.00	0.86	0.78	0.82	-0.03
FF5 alpha	0.25	0.25	0.01	0.02	0.01	0.01	0.00	-0.01	0.00	-0.01	0.02	0.00	0.10	0.70	0.94	0.86	1.00	0.78	0.81	-0.01
QF alpha	0.26	0.26	0.01	0.03	0.03	0.02	0.03	-0.05	0.01	-0.03	-0.03	0.00	0.09	0.76	0.78	0.78	0.78	1.00	0.80	-0.13
MF alpha	0.26	0.26	0.01	0.01	0.01	0.01	0.00	-0.01	0.00	-0.03	-0.01	0.00	0.09	0.74	0.83	0.82	0.81	0.80	1.00	-0.04
Beta MKT CAPM	-0.02	-0.02	-0.04	-0.16	-0.09	0.03	-0.08	0.15	-0.02	0.17	0.35	0.03	-0.25	-0.03	-0.04	-0.03	-0.01	-0.13	-0.04	1.00

Figure 4-1 Aggregate SDR, Fund Flows and Market Returns

This figure shows aggregate smart-to-dumb ratio (SDR), aggregate fund flows and SPX500 index returns from 2004 to 2016. SDR is defined as the decomposed R-squared of fundamental fund characteristics divided by the decomposed R-squared of exotic risk-adjusted performance. Aggregate fund flow is average flow across funds in each year. The SPX500 index return is the total return from the SPX500 index.

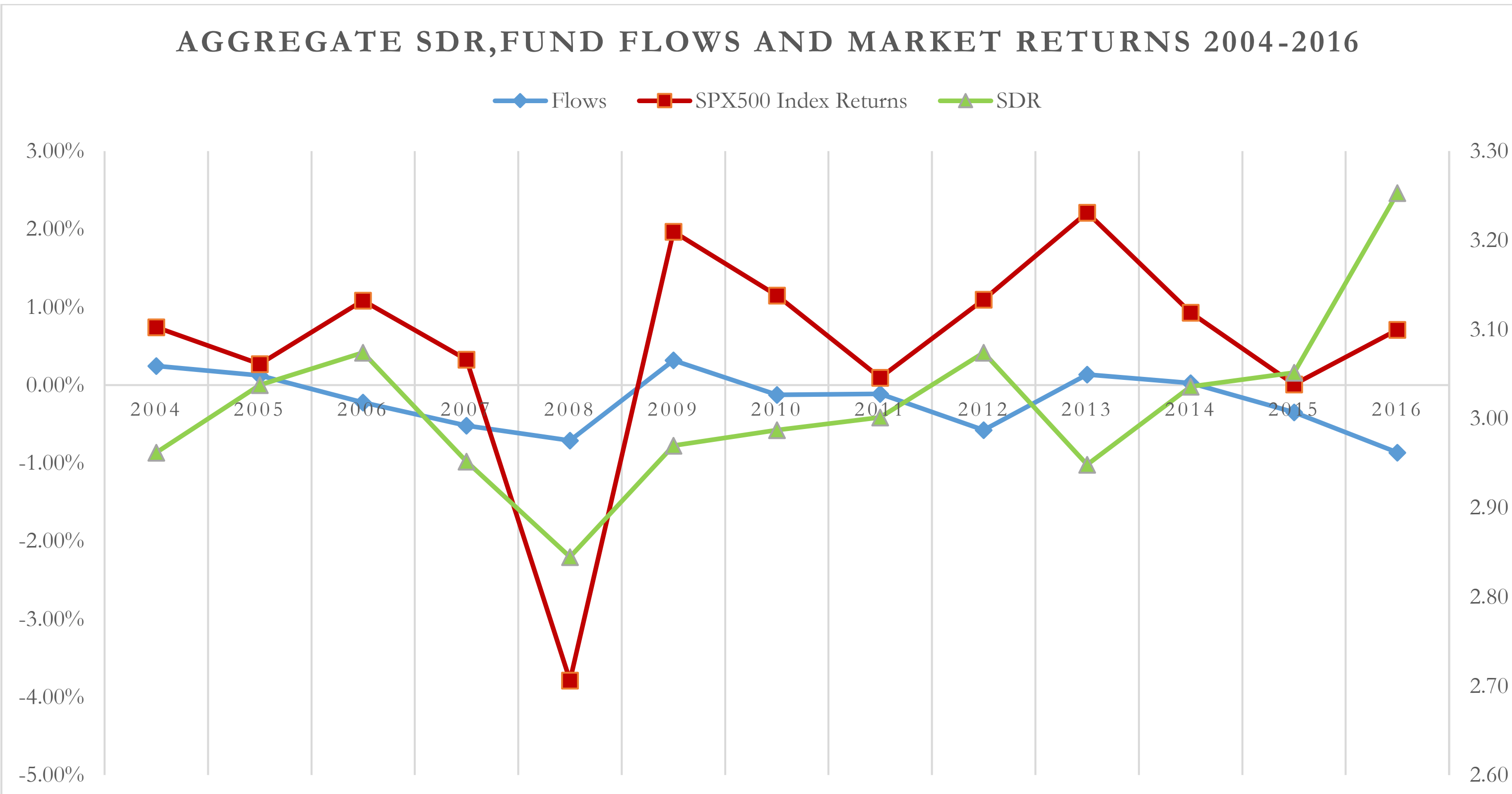


Table 4-2 shows summary statistics for the US sample. The sample covers 1946 actively-managed domestic equity funds in the US whose assets under management reach a ten-million threshold and have existed for at least five years. I provide risk-adjusted alpha from the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model and the Fama-French five-factor, the Q-factor model and the Stambaugh-Yuan mispricing-factor model with 60-month rolling window regressions. I summarize risk-adjusted alphas and risk betas from these six asset pricing models. For the performance implications in Section 4.7, I propose a Smart-to-Dumb Ratio based on decomposed R-squared in the following analysis and I report its statistics in Table 4-2 Panel A as well.

In Panel A, I report descriptive statistic for decomposed R-squared, fund characteristics, Morningstar ratings, risk-adjusted performance and risk-adjusted betas of the whole sample. The Smart-to-Dumb Ratio (SDR) has a mean of 3. It indicates that, on average, the explanatory power of fundamental fund characteristics for fund flows is three times larger than that of exotic risk-adjusted performance. As for performance, on average, CAPM alpha is close to zero (-0.08%), and CAPM beta has a mean of 1.06, it ranges from 0.28 to 2.57. For fund characteristics, the mean of fund size (TNA) is 2,031.54 million, and its median is 485.52 million. On average, the sample funds charge their investors fees of 1.19% and average annual turnover and average volatility are 69% and 4% respectively. Average Morningstar 3-year and 5-year ratings are about 3. The sample is comparable to other fund flow studies in terms of expenses, fund turnover and volatility (e.g., Franzaoni and Schmalza, 2017; Huang, Wei and Yan, 2007). In Figure 4-1, I plot SDR with SPX 500 index returns and aggregate mutual fund flows. The trend demonstrates that aggregate SDR might potentially affect aggregate market returns, as measured by the SPX500 index.

4.4.2 Mutual Fund Flows

I follow Coval and Stafford (2007) and Barber, Huang and Odean (2016) and define the dependent variable, quarterly fund flows, as

$$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t})}{TNA_{i,t-1}}$$

(Eq. 4-1)

Where $TNA_{i,t}$ is the total net assets of fund *i* in quarter *t*, $RET_{i,t}$ is the return of fund *i* in quarter *t*, obtained from quarterly fund reports. Follow Franzoni and Schmalz (2017), fund flow, expense ratio, turnover ratio and return volatility are winsorized at the 1st and 99th percentiles. Regarding the data source, CSMAR fund database covers comprehensive fund characteristics in China and it is guaranteed to be free of survivorship bias. In addition, Morningstar comprises comprehensive US mutual fund data and it is also guaranteed to be free of survivorship bias (Berk and Van Binsbergen, 2015). It is also free of the problem of overstating returns for months with multiple distributions on the same day (Elton, Gruber and Blake, 2001).

4.4.3 Risk Models for Mutual Funds' Risk-Adjusted Performance

To measures mutual funds' risk-adjusted returns, for the Chinese market, I use monthly fund returns data to estimate beta and alpha from a range of risk models, including the capital asset pricing model (CAPM), Fama-French three-factor model and the Fama-French-Carhart model which have been studied in previous literature (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016). I also included the Fama-French five-factor model and the Q-factor model from Hou, Xue and Zhang (2014). Then, I use 24-month rolling windows to estimate the parameters. I employ monthly return data for sample funds to calculate abnormal returns for the period 2004-2016.

For the US market, I also include the mispricing-factor model from Stambaugh and Yuan (2016).[13] I estimate rolling windows of 60 months (5 years) from *t*-1 to *t*-60 using the CAPM, Fama-French three-factor model, Fama-French-Carhart model, Fama-French five-factor model and Q-factor model from Hou, Xue and Zhang (2014).[14] I require funds to have at least three years of historical data, so a fund must have a least 36 months of observations for each 60-month window (Akbas et al., 2016).

For the calculation of risk-adjusted returns, first, I obtain parameters as the coefficient of each risk factor and utilize them to calculate out-of-sample alpha in month t. In the case of the Fama-French-Carhart model, I run regressions using returns from months τ=*t*-1 to *t*-24/*t*-60: [15]

$$R_{i,\tau} - R_{f,\tau} = \alpha_{i,t} + \beta_{1,t} * \left(R_{m,\tau} - R_{f,\tau}\right) + \beta_{2,t} * SMB_{\tau} + \beta_{3,t} * HML_{\tau} + \beta_{4,t} * UMD_{\tau} + \varepsilon_{i,\tau}$$

[13] Mispricing factors are collected from the website of Professor Robert F. Stambaugh.

[14] I take 24-month and 60-month rolling windows for both China and the US. Considering the numbers of funds and sample observations, I choose 24-month windows for China and 60-month windows for the US. The results are similar if I take 24-month windows for the US market. I keep the 60-month windows for the US to maintain consistency with existing US studies.

[15] I conduct risk-adjusted return calculations without industry factors. This is different to the risk-adjusted return calculations from Barber, Huang and Odean (2016). They utilize the principle component analysis (PCA) method to extract the top three industry components. As the main components of industry factors have a close relation to market returns, this might cause autocorrelations in risk-adjusted return calculations, so I exclude industry factors from return calculations.

where $R_{i,\tau}$ is the mutual fund return of fund *i* in month τ, $R_{f,\tau}$ is the risk-free rate, $R_{m,\tau}$ is the market portfolio return, SMB_{τ} is the size factor, HML_t is the value factor, and UMD_t is the momentum factor.

Second, I use parameter estimates that estimate over 24-month or 60-month before month *t* to calculate abnormal returns at time *t* as realized returns less the risk exposure of funds to risk factors in the six assets pricing models. In the case of the Fama-French-Carhart model, the risk-adjusted alpha is calculated as follows:

$$\widehat{\alpha_{i,t}} = (R_{i,t} - R_{f,t}) - [\widehat{\beta_{1,t}} * \left(R_{m,t} - R_{f,t}\right) + \widehat{\beta_{2,t}} * SMB_t + \widehat{\beta_{3,t}} * HML_t + \widehat{\beta_{4,t}} * UMD_t]$$

I repeat this procedure for all months of each fund and obtain a times series of monthly alpha and betas in the sample.

For the US market, I also adjust the risk-adjusted alphas with horizons. Investors may react to new information with certain time delays. Following Barber, Huang and Odean (2016), I address the horizons for performance evaluation. As investors respond to new information and balance its relevance to their decisions, I consider a horizon of 18 months as the evaluation period based on the Akaike information criterion (AIC) of models. I compound risk-adjusted alphas with an 18-month horizon and take the weighted average. The weight is based on the decay rate obtained by regressing monthly fund flows $F_{i,t}$ on market excess returns MAR_{t-s}. Control variables include lagged expense ratio, a dummy variable for no-load funds, prior twelve-month return volatility, the log of fund size, fund age and lagged fund flows in month *t*-19. I also set month dummies to control for the time fixed effect with μ_t. I list the models for the horizon adjustment as follows:

Unrestricted model:

$$F_{i,t} = \alpha + \sum_{S=1}^{18} \beta_s MAR_{\,i,t-s} + \gamma \mathrm{X}_{i,t} + \mu_t + \varepsilon_{i,t}$$

Exponential decay model:

$$F_{i,t} = \alpha + \beta \sum_{S=1}^{18} e^{-\lambda(s-1)} MAR_{\,t-s} + \gamma \mathrm{X}_{i,t} + \mu_t + \varepsilon_{i,t}$$

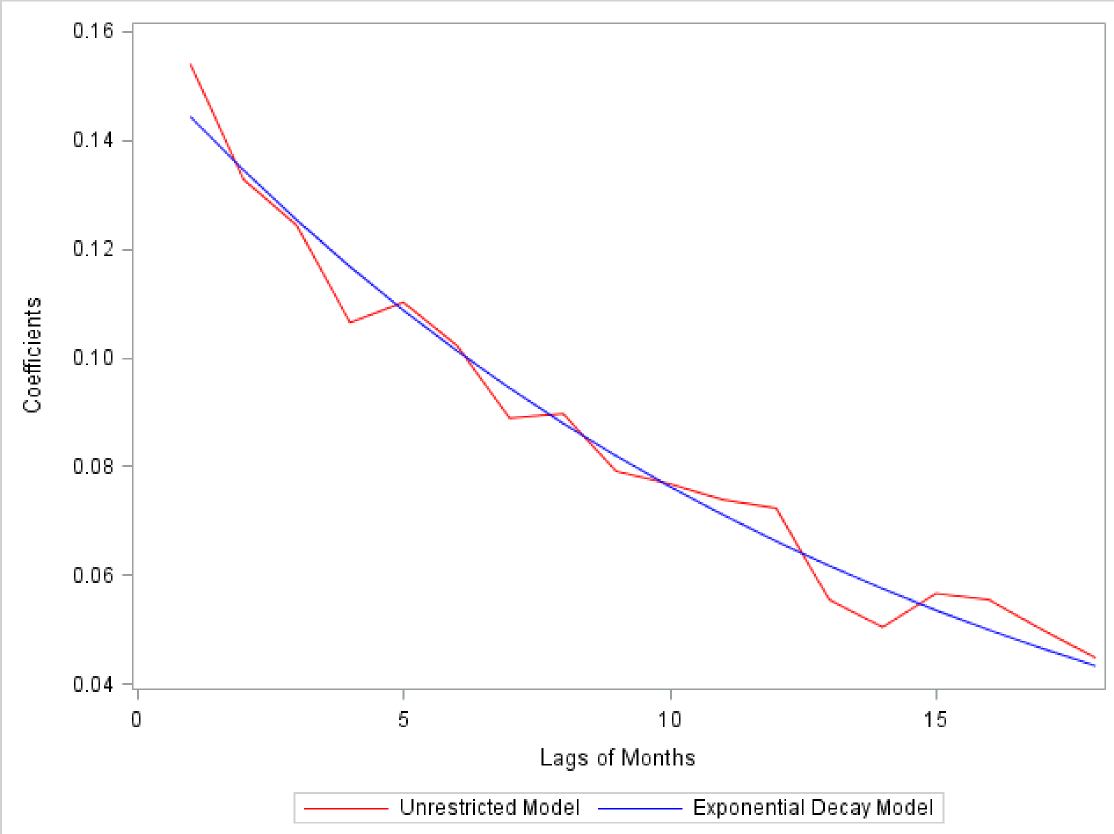
Alphas:

$$Alpha_{i,t} = \frac{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)} \widehat{\alpha_{t-s}}}{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}}$$

Figure 4-2 Horizon Adjustment for Risk-Adjusted Alphas

This figure shows regression coefficients in the horizon adjustment for risk-adjusted alphas. I take 18 months as the evaluation period based on the AIC information criterion. Utilizing the regression of fund flows on market excess returns in the following 18 months, the unrestricted model shows 18 coefficients for each lag. The exponential decay model adjusts the coefficients with an exponential decay function following Barber, Huang and Odean (2016).

Figure 4-2 (continued)



4.4.4 Measuring Managers' Skills in Active Management

Prior literature documents a number of proxies for measuring active management skills. I mainly focus on proxies constructed with funds' holding from these perspectives: diversification, industry concentration index, reliance on public information, fund-report attention, active share and return gap.

Diversification: It is measured by the number of stocks held by a fund in each quarter following Pollet and Wilson (2008). A larger number of stocks in a fund portfolio indicates greater diversification. Pollet and Wilson (2008) find that fund diversification is positively related to future fund performance, especially in small-cap funds.

Industry Concentration Index (ICI): Industry concentration index, introduced by Kacperczyk, Sialm and Zheng (2005), is a measure of the industry concentration of a fund's portfolio, it is the sum of squares of difference between a fund's weight in a particular industry and the weight of the industry size in the whole market portfolio. A higher industry concentration indicates that a fund only invests in a relatively small number of industries. Kacperczyk et al. (2005) find that, on average, funds with a higher concentration perform better as funds may have superior information in specific industries.

Reliance on Public Information (RPI): Reliance on public information, initiated by Kacperczyk and Seru (2007), is a measure of the change in a fund portfolio in response to stock recommendations provided by stock analysts (public information). A higher RPI indicates less private or superior information traded by fund managers so that a fund follows the common recommendations of stock analysts to allocate their money. Kacperczyk and Seru (2007) show that a larger RPI indicates a decrease in management skills and it is negatively related to future fund performance and future capital flows.

Fund-Report Attention: It is equal-weighted analyst report coverage of holding stocks, provided by the CSMAR database. Higher attention implies greater analyst coverage of fund holdings. Sirri and Tufano (1998) find that funds with greater attention from the media can reduce the search cost of funds; then, they can attract more money flows. Also, analysts' coverage affects stock prices (Zhang, Cai and Keasey, 2013) and subsequently interacts with the information supply of active management

(Kacperczyk and Seru, 2007). I include fund-report attention in the active measures group.

Active Share: Active share, introduced by Cremers and Petajisto (2009), is a measure of the deviation of the stock weight held by a fund from its weight on the fund's benchmark. A higher active share indicates greater portfolio activeness. If active share is zero, it means that a fund has the same portfolio as its benchmark. If it is equal to one, it indicates that the fund holds stocks that are entirely different from its benchmark. Cremers and Petajisto (2009) find that funds with high active shares can outperform their benchmarks and have persistent performance.

Return Gap: Return gap measures the difference between reported returns and returns calculated from holdings. It is a proxy for the unobserved actions of mutual funds (Kacperczyk, Sialm and Zheng, 2008). They show that return gaps positively predict fund performance in the US mutual fund market. They suggest that return gap measures the skill of managers in dealing with market timing and reduce hidden costs (e.g., commission fees paid to brokers).[16]

4.4.5 Fundamental Fund Characteristics

The literature also abundantly documents a number of proxies of fundamental fund characteristics. I mainly focus on proxies with empirical studies to support them. I take

[16] As portfolio holdings do not capture the exact trading date of funds, fund managers might window dress their portfolios so that they hide their holdings by liquidating them or purchasing new stocks at the reported date (Agarwal, Gay and Ling, 2014). The return gap measure is subject to some measurement errors. However, return gap is not merely determined by holding returns. It is constructed using the difference between fund returns and holding returns. The calculation of return gap alleviates this issue (Kacperczyk, Sialm and Zheng, 2008). I acknowledge this issue and follow the method from Kacperczyk, Sialm and Zheng (2008) to construct the return gap.

fund characteristics, including fund size, fund family size, fund age, fund fee, lagged fund flow and return volatility.

Fund Size: Fund size is the total net assets of a fund in each quarter. Fund size has been found to be negatively related to future fund flows (Sirri and Tufano, 1998; Huang, Wei and Yan, 2008). Also, some studies document that fund size erodes fund performance and industry performance, which might indirectly and negatively affect fund flows (Chen et al., 2004; Pástor, Stambaugh and Taylor, 2015).

Family Size: Fund family size is the sum of a funds' size in each quarter. Sirri and Tufano (1998) claim that funds with a larger family size have lower search cost and can attract greater money inflows. Huang, Wei and Yan (2008) further find that funds with moderately good performance in larger fund families can attract more money inflows. Also, Bhojraj, Cho and Yehuda (2012) find that fund family size is positively associated with fund performance.

Fund Age: It measures the number of quarters (or number of months) since a fund launched. Chevallier and Ellison (1997) find that young funds can beat the market and enjoy greater money inflows. In addition, Pástor, Stambaugh and Taylor (2015) find that young funds tend to outperform old funds since the growth of the active management industry brings more skilled competition.

Fund Fees: They are measured as the total operating costs divided by total net assets in China due to data availability. In the US market, I take annual expense ratios from Morningstar database. It has been found that the expense ratio positively predicts performance (Sheng, Simutin and Zhang, 2017). Also, Barber, Odean and Zheng (2005) find that investor flows are negatively related to front-end load and commission.

However, when splitting the total expense ratio into marketing expenses (12B-1) and other fees, investors are more likely to buy a fund with higher marketing expenses.

Lagged Fund Flow: Lagged fund flow is the fund flow from the previous quarter, measured as the growth rate in fund total net asset (TNA), net of capital gain (return). Zheng (1999) find that mutual fund investors can pick better funds and that funds with higher money inflows outperform their peer funds with lower inflows. Keswani and Stolin (2008) also find the smart money effect exist in the UK market. If investors can recognize smart money, they can utilize lagged flows as a signal to allocate their money in mutual fund selection.

Return Volatility: Return volatility is the standard deviation of a fund's previous 12-month returns. Sirri and Tufano (1998) find that mutual fund flows are not monotonically related to return volatility and funds with return volatility in the top or bottom deciles have greater money inflows. It also has been found that return volatility affects fund flows (Huang, Wei and Yan, 2008; Barber, Odean and Zheng, 2005).

4.4.6 Decomposed R-squared

To decompose R-square, I follow the approach of Hüttner and Sunder (2011). The intuition is that I apply Shapley-Owen values to measure the marginal contribution of each regressor to the goodness of fit in a multiple-factor regression. In cooperative game theory, Shapley (1953) values allow us to distribute the total gains of players in cooperation fairly. Utilizing Shapley values in regression analyses, I can decompose the goodness of fit. Researchers use Shapley values to measure the marginal contribution of each independent variable in explaining the dependent variable (Chevan and Sutherland, 1991; Johnson and LebRreton, 2004). Furthermore, in many practical cases, a group of independent variables represent similar explanatory meaning. Owen (1997) values offer a solution to calculate the marginal contribution of group regressors, which are exogenously defined (Shorrock, 2013; Huntter and Sunder, 2011).

I compute the Shapley value of each regressor that measures a marginal contribution to R-squared by adding the regressor to the model, which is weighted by the number of permutations in the submodel (Franzoni and Schmalz, 2017; Israeli, 2007; Devicienti, 2010; Sastre and Trannoy, 2002). The individual R-squared of regressor x_i is calculated by

$$R_i^2 = \sum_{T \subseteq z \setminus \{x_i\}} \frac{k! * (p-k-1)!}{p!} [R^2(T \cup \{x_i\}) - R^2(T)]$$

Where T is the model excluding regressor x_i, $T \cup \{x_i\}$ is the same model including x_i, k is the number of regressors in the model T, and p is the number of regressors in the main model. In decompositions. I treat each regressor as a player in a cooperative game and regard the goodness of fit or overall R-squared from one regression as gains from this cooperative game. I calculate marginal contribution or Shapley value (Shapley, 1953) for each regressor to distribute gains (decomposed R-square). As researchers might believe some regressors belong to one group to explain the dependent variable together, I set limits in calculations of marginal contributions (Owen, 1997) and obtain the Shapley-Owen value. The individual R-squared of each independent variable is extracted from each regression in the above equation. I sum the R-squared in each group to get alpha R-square, beta subtotal R-squared, active subtotal R-squared and fundamental subtotal R-squared.

4.5 Empirical Results

This section reports my empirical results. I start the analysis by studying which models are mainly employed by investors in China, following the tests proposed by Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016).

4.5.1 Risk Model Performance Test in China

4.5.1.1.1 Model Performance Test by Berk and Van Binsbergen (2016)

To find out which models investors employ in fund selection, I begin by examining how fund flows respond to alphas calculated from different risk models. Berk and Van Binsbergen (2016) argue that a superior risk model should fit mutual fund flows. By regressing the sign of fund flow on the sign of model alpha, this model performance test examines the direction of risk-adjusted alpha and fund flow from the coefficient:

$$\beta_i = \frac{cov(\phi(flow_{i,t}),\phi(\varepsilon_{i,t}))}{var(\phi(\varepsilon_{i,t}))}$$

(Eq. 4-2)

Where $flow_{i,t}$ is the flow of fund *i* in quarter *t*, $\varepsilon_{i,t}$ is the alpha of fund *i* in quarter *t*, and ϕ is the sign function. If the sign of the flow is equal to the sign of the model alpha for most of the funds in the whole sample period, it indicates that the model is mostly used by investors to allocate their money to funds. From Equation 4-2, I find that if β_i is equal to 1, it indicates that the sign of flow always has the same sign as alpha. A large β_i implies that the risk model has produced right signals followed by fund flows. I also extend this analysis by including the Q-factor model from Hou, Xue and Zhang (2014) and the five-factor model from Fama and French (2015).

Table 4-3 Flow of Funds Model Performance Test

This table reports the probability of $\frac{1+\beta_f}{2}$ in the test developed by Berk and Van Binsbergen (2016). I get the sign series of flow and model performance and run a univariate ordinary least square (OLS) regression to get the coefficients. The first row reports the performance of CAPM using the CSMAR value-weighted index as the market factor. The "no model" series contains: (1) return of the fund (Return) (2) return in excess of risk-free rate (ExRet) (3) return in excess of CSMAR value-weighted market return (ExMkt). The multifactor models contain the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF). I run the test from a three-month horizon to a five-year horizon.

3-month		6-month		1-year		2-year	
Model	Performance	Model	Performance	Model	Performance	Model	Performance
CAPM	68.58%	CAPM	67.13%	CAPM	65.38%	CAPM	63.12%
FF3	68.18%	ExMkt	66.94%	ExMkt	64.79%	QF	62.62%
FF4	68.03%	FF3	66.48%	QF	64.52%	ExMkt	61.70%
ExMkt	67.91%	FF4	65.86%	FF3	63.91%	FF5	61.02%
FF5	67.40%	FF5	65.44%	FF5	63.49%	FF3	60.71%
QF	67.16%	QF	64.88%	FF4	63.42%	FF4	60.58%
Return	53.59%	Return	54.55%	ExRet	52.39%	ExRet	50.79%
ExRet	53.59%	ExRet	54.20%	Return	51.99%	Return	50.20%

3-year		4-year		5-year	
Model	Performance	Model	Performance	Model	Performance
CAPM	61.81%	CAPM	59.72%	QF	58.44%
QF	60.81%	QF	59.45%	CAPM	57.23%
FF4	60.53%	FF4	59.20%	FF4	57.19%
FF3	59.83%	FF3	58.10%	FF3	56.31%
FF5	59.54%	FF5	57.50%	FF5	55.51%
ExMkt	58.40%	ExRet	55.54%	ExRet	54.83%
Return	54.06%	Return	54.62%	Return	52.57%
ExRet	53.11%	ExMkt	53.00%	ExMkt	46.53%

Table 4-3 reports the results. To illustrate them, for example, over a 3-month horizon, CAPM has the highest performance of 68.58%, which suggests that the sign of flow has the highest probability to have the same sign as CAPM alpha. Based on Table 4-3, I have the following findings:

First, CAPM outperforms all factor models in China over 3-month to 4-year horizons which implies the dominance of CAPM across factor models. It is consistent with Hypothesis One (H1) and the US findings of Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016). Furthermore, the second best risk model is the Q-factor model (QF) from Hou, Xue and Zhang (2014). The traditional Fama-French three-factor and four-factor models often feature in the third place, suggesting they are relevant to some investors' considerations. This indicates that the Fama-French series might be the industry standard for investors to price risk in the short term (within six months), while investors tend to rely on Q-factor in the long term (over one year). In addition, CAPM also outperforms "ExMkt" over all horizons, which implies that investors do use market beta from CAPM to adjust systematic risk. Next, "ExMkt" model underperforms risk models over a 2-year horizon, which indicates that investors are more sensitive to risk in the long term. It might also suggest that within the short term (less than two years) investors refer to a less sophisticated model or employ non-risk factors in their fund decisions.

Second, within "no model" group, "Return" model indicates that people choose funds merely based on past performance. Next, if investors are risk-neutral, and they only consider performance relative to the risk-free rate, "ExRet" model will outperform other models. In addition, if investors do not adjust for risk difference (beta) between fund returns and market returns, then fund returns in excess of market returns (ExMkt) will outperform other risk factor models. From Table 4-3, "ExMkt" outperforms other "no models" over 3-month to 3-year horizons. The success of "ExMkt" might be attributed to the limited information supply of retail investors. For example, in most fund prospectuses, benchmark adjusted-returns are widely reported to disclose the period performance of mutual funds. This is consistent with Ivković and Weisbenner (2009) in that individual inflows are sensitive to "relative" performance, so investors might intuitionally judge funds from the curve for relative outperformance. [17]

4.5.1.1.2 Test of Statistical Significance by Berk and Van Binsbergen (2016)

To confirm results in Section 4.5.1.1.1, I test their significance from the fund level, the time level and the intersection of fund level and time level. Table 4-4 shows the *t*-statistics adjusted by double-clustered standard errors (Thompson, 2011 and Peterson, 2009). First, following Equation 4-3, I run univariate regressions to get coefficients by regressing the sign of fund flows on the sign of fund performance adjusted by each model.

$$\phi(\mathrm{F}_{it}) = \gamma_0 + \gamma_1 \phi(\varepsilon_{it}) + \xi_{it}$$

(Eq. 4-3)

$$\phi(\mathrm{F}_{it}) = \gamma_0 + \gamma_1 \left\{ \frac{\phi(\varepsilon_{it}^{c})}{var(\phi(\varepsilon_{it}^{c})} - \frac{\phi(\varepsilon_{it}^{d})}{var(\phi(\varepsilon_{it}^{d})} \right\} + \xi_{it}$$

(Eq. 4-4)

[17] I did similar robustness tests to Berk and Van Binsbergen (2016), comparing the relative performance of risk models. Similar results indicate that the CAPM outperforms other risk models.

Where F_{it} is the fund flow of fund *i* in quarter *t*, ε_{it} is the performance of fund *i* in quarter *t*, $\phi()$ is a sign function, $var()$ is a function to calculate variances. ε_{it}^{c} is the performance of fund *i* at quarter *t* that is adjusted with model *c*, ε_{it}^{d} is the performance of fund *i* at quarter *t* that is adjusted with model *d*.

Table 4-4 Test of Statistical Significance

This table shows the statistical significance of each model. The first two columns report the coefficients and double-clustered *t*-statistics from the univariate regressions of Equation 4-3. The rest of columns report the double-clustered *t*-statistics of γ_1 from Equation 4-4 in pairwise tests. If the "t-stat" is statistically negative, it indicates that the model *c* in the top row is significantly better than the model *d* in the left column.

					3-month horizon					
Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.29	9.58		-0.47	-0.51	-0.06	0.26	5.19	5.19	1.70
FF	0.30	10.69	0.47		-0.19	1.62	0.70	5.89	5.91	1.38
FF4	0.30	10.84	0.51	0.19		0.91	0.74	5.87	5.92	1.38
FF5	0.29	11.06	0.06	-1.62	-0.91		0.34	5.44	5.42	1.07
QF	0.28	9.96	-0.26	-0.70	-0.74	-0.34		5.38	5.41	0.60
Return	0.05	1.01	-5.19	-5.89	-5.87	-5.44	-5.38		-0.81	-3.95
ExRet	0.06	1.12	-5.19	-5.91	-5.92	-5.42	-5.41	0.81		-3.90
ExMkt	0.26	8.29	-1.70	-1.38	-1.38	-1.07	-0.60	3.95	3.90	

					6-month horizon					
Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.28	12.33		-0.07	-0.19	1.29	1.44	5.13	5.41	0.84
FF	0.28	12.35	0.07		-0.35	3.28	1.45	5.03	5.21	0.76
FF4	0.28	12.68	0.19	0.35		2.28	1.55	5.07	5.32	0.76
FF5	0.27	11.83	-1.29	-3.28	-2.28		0.64	4.29	4.46	-0.17
QF	0.25	9.60	-1.44	-1.45	-1.55	-0.64		3.80	4.13	-0.56
Return	0.06	1.19	-5.13	-5.03	-5.07	-4.29	-3.80		0.34	-3.75
ExRet	0.06	1.23	-5.41	-5.21	-5.32	-4.46	-4.13	-0.34		-3.87
ExMkt	0.26	9.87	-0.84	-0.76	-0.76	0.17	0.56	3.75	3.87	

Table 4-4 (continued)

1-year horizon											
Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.26	10.92		1.49	-0.68	2.31	0.86	5.69	5.42	0.17
FF	0.25	11.85	-1.49		-2.23	1.59	-0.07	4.35	3.81	-0.51
FF4	0.26	11.32	0.68	2.23		3.63	0.85	6.19	5.43	0.39
FF5	0.24	11.81	-2.31	-1.59	-3.63		-0.60	2.11	1.95	-0.88
QF	0.26	9.94	-0.86	0.07	-0.85	0.60		3.79	3.57	-0.45
Return	0.05	1.49	-5.69	-4.35	-6.19	-2.11	-3.79		-1.42	-3.49
ExRet	0.07	1.80	-5.42	-3.81	-5.43	-1.95	-3.57	1.42		-3.23
ExMkt	0.21	7.45	-0.17	0.51	-0.39	0.88	0.45	3.49	3.23	

2-year horizon										
Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.24	10.19		1.61	0.00	0.85	2.83	5.81	5.12	0.36
FF	0.21	10.07	-1.61		-1.47	-0.52	1.48	3.18	2.76	-0.09
FF4	0.22	10.44	0.00	1.47		0.71	3.44	5.47	4.93	0.48
FF5	0.22	10.57	-0.85	0.52	-0.71		1.73	3.53	2.99	0.24
QF	0.24	8.27	-2.83	-1.48	-3.44	-1.73		2.02	1.38	-0.94
Return	0.05	1.59	-5.81	-3.18	-5.47	-3.53	-2.02		-0.28	-2.93
ExRet	0.06	1.76	-5.12	-2.76	-4.93	-2.99	-1.38	0.28		-2.62
ExMkt	0.16	4.23	-0.36	0.09	-0.48	-0.24	0.94	2.93	2.62	

3-year horizon										
Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.22	8.15		1.14	1.63	2.31	2.52	2.05	2.95	2.31
FF	0.19	8.00	-1.14		-0.05	0.62	0.60	0.80	1.80	1.37
FF4	0.21	8.50	-1.63	0.05		0.96	0.59	0.89	1.87	1.20
FF5	0.18	7.97	-2.31	-0.62	-0.96		-0.21	0.28	0.86	1.37
QF	0.23	6.13	-2.52	-0.60	-0.59	0.21		-1.03	-0.55	0.52
Return	0.12	3.35	-2.05	-0.80	-0.89	-0.28	1.03		2.78	0.76
ExRet	0.11	3.46	-2.95	-1.80	-1.87	-0.86	0.55	-2.78		0.37
ExMkt	0.10	1.98	-2.31	-1.37	-1.20	-1.37	-0.52	-0.76	-0.37	

4-year horizon										
Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.19	6.31		0.92	1.91	1.85	1.02	-0.31	1.25	1.84
FF	0.17	6.64	-0.92		-0.14	3.96	-0.68	-2.71	-1.02	0.64
FF4	0.19	7.48	-1.91	0.14		1.24	0.09	-2.45	-0.36	0.48
FF5	0.16	6.47	-1.85	-3.96	-1.24		-3.24	-3.56	-1.85	0.27
QF	0.20	5.00	-1.02	0.68	-0.09	3.24		-2.84	-1.49	-0.67
Return	0.13	3.52	0.31	2.71	2.45	3.56	2.84		5.80	1.44
ExRet	0.15	4.11	-1.25	1.02	0.36	1.85	1.49	-5.80		0.50
ExMkt	0.02	0.38	-1.84	-0.64	-0.48	-0.27	0.67	-1.44	-0.50	

Table 4-4 (continued) 5-year horizon

Model	Coeff.	*t*-stat	CAPM	FF	FF4	FF5	QF	Return	ExRet	ExMkt
CAPM	0.15	4.32		1.05	0.50	1.92	0.80	-0.10	-0.14	2.36
FF	0.13	4.84	-1.05		0.51	2.03	-0.63	-0.22	-1.84	1.71
FF4	0.14	5.03	-0.50	-0.51		0.52	0.62	0.05	-1.13	1.90
FF5	0.11	4.27	-1.92	-2.03	-0.52		-1.36	-1.22	-2.46	1.71
QF	0.17	3.52	-0.80	0.63	-0.62	1.36		0.16	-1.19	-0.33
Return	0.05	1.16	0.10	0.22	-0.05	1.22	-0.16		0.84	1.65
ExRet	0.10	2.33	0.14	1.84	1.13	2.46	1.19	-0.84		1.48
ExMkt	-0.07	-0.96	-2.36	-1.71	-1.90	-1.71	0.33	-1.65	-1.48	

From the first two columns in Table 4-4, I find that fund flows do react to risk-adjusted performance from the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model, the Fama-French five-factor model and the Q-factor model with statistically significance from 3-month to 5-year horizon. The double-clustered *t*-statistics of risk model are significant at the 1% level. For the CAPM at the 1-year horizon, it has a coefficient of 0.26 (t=10.92). CAPM alpha has the largest coefficient from one to five years. The coefficient of the CAPM is close to the coefficients of Fama-French models at the 3-month and 6-month horizon.

Then, I then test the pairwise performance between models using Equation 4-4 from Berk and Van Binsbergen (2015). If the *t*-statistic of γ_1 is negative (positive), it implies that the model in the top row (model c) outperforms (underperforms) the model in the left column (model d). For example, in Panel B of Table 4-4, at the 3-year horizon, the *t*-statistic of the CAPM to the Fama-French five-factor model (FF5) is -2.31. It indicates that the CAPM significantly outperforms the Fama-French five-factor model at the 5 % significant level. I find that the CAPM has a negative *t*-statistic over all horizons, but it does not show strong significance over all horizons.

Taken together, results from Table 4-4 support that CAPM outperforms other risk models in driving fund flows. However, their statistical significances are not strong at all horizons. Next, I utilize the pairwise performance test from Barber, Huang and Odean (2016) to further examine it.

4.5.1.2 Model Performance Test from Barber, Huang and Odean (2016)

Table 4-5 Pairwise Model Performance Test

This table shows the results of a pairwise comparison test by Barber, Huang and Odean (2016). The table examines the hypothesis that if the sum of coefficient differences is significantly different from zero. A positive and significant sum indicates that Model A performs better than Model B. ***, ** and * denote significance at 1%, 5% and 10% levels respectively.

Panel A: CAPM vs other models

Model A	CAPM	CAPM	CAPM	CAPM	CAPM	CAPM	CAPM
Model B	Return	ExRet	ExMkt	FF3	FF4	FF5	QF
Sum of coefficient difference	1.07***	1.24***	1.25***	1.31**	2.07***	1.32**	1.46***
% of coefficient differences >0	71.11%	71.11%	71.11%	64.44%	75.56%	48.89%	75.56%
t-stat	(3.84)	(4.17)	(4.16)	(2.46)	(3.60)	(2.41)	(4.08)
Binominal p-value	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***

Panel B: ExMkt vs other models

Model A	ExMkt	ExMkt	ExMkt	ExMkt	ExMkt	ExMkt	ExMkt
Model B	CAPM	Return	ExRet	FF3	FF4	FF5	QF
Sum of coefficient difference	-1.25***	-0.82	-0.02	-0.60**	-0.53***	-0.41**	-0.17
% of coefficient differences >0	28.89%	35.56%	20.00%	28.89%	33.33%	44.44%	57.78%
t-stat	-(4.16)	-(0.60)	-(0.04)	-(2.52)	-(2.64)	-(2.25)	-(0.95)
Binominal p-value	<0.0001***	<0.0004***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***

Panel C: FF3 vs other models

Model A	FF3	FF3	FF3	FF3	FF3	FF3	FF3
Model B	CAPM	Return	ExRet	ExMkt	FF4	FF5	QF
Sum of coefficient difference	-1.31**	0.45*	0.63***	0.60**	0.97	1.12	1.48***
% of coefficient differences >0	35.56%	62.22%	68.89%	71.11%	64.44%	64.44%	75.56%
t-stat	-(2.46)	(1.92)	(2.96)	(2.52)	(1.18)	(1.45)	(4.00)
Binominal p-value	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***

To further confirm the dominance of CAPM, I conducted a pairwise model performance test from Barber Huang and Odean (2016). They argue that investors should consider all factors whether priced or unpriced, in their investment decisions. To identify the asset pricing models used by mutual fund investors, they conducted a test by competing one model against another. If investors react to a model with consistently larger coefficients under different deciles of model alpha than the alpha of other models, the alpha of this model is a better predictor of fund flows. They found that CAPM alpha is the best predictor in modelling fund flows as it outperforms other risk-adjusted alphas or factor-related returns. Sophisticated investors react less to common factor-related returns, indicating that they might have advanced factors to trade, such as option-based, commodity-based and foreign exchange factors.

Specifically, I follow Barber, Huang and Odean (2016) to conduct a test based on the flow-alpha sensitivities (coefficient) of different risk models by estimating the following regressions:

$$\mathrm{Flow}_{pt} = \alpha + \sum_i \sum_j b_{ij} \, D_{ijpt} + cX_{pt} + u_t + \varepsilon_{pt} \quad (3)$$

(Eq. 4-5)

Where Flow_{pt} is the flow of fund *p* in quarter *t*, D_{ijpt} is a dummy variable that is equal to one if the fund alpha in quarter *t* is in decile *i* based on the first model, and if the fund alpha is in decile *j* based on the second model. The control matrix X_{pt} includes lagged fund flows in quarter *t*-1, the log of fund size, prior 12-month return volatility and the log of fund age. The test sorts funds into deciles based on risk-adjusted alphas. If investors react to the risk-adjusted alpha of a model under different deciles with relatively large coefficients, they may employ this model in fund selection.

The results in Table 4-5 also shows that the CAPM outperforms all other models. The CAPM proves significantly to be the best predictor of fund flows with the highest coefficients. To illustrate the method, to compare CAPM alpha and FF4 alpha, I regress flows on a dummy variable that indicates funds which are ranked on the 3rd decile CAPM alpha and the 6^{th} decile of FF4 alpha. I obtain coefficient β_1 from the regression. Then, I regress flows on a dummy variable that indicates funds, which are ranked on the 3^{rd} decile of FF4 alpha and the 3^{rd} decile of CAPM. I obtain coefficient β_2 from the regression. I take $\beta_1 - \beta_2$ as the difference of the case (decile 3 and decile 6). If these two models are the same, the difference $\beta_1 - \beta_2$ in each case will be zero. Following the same approach, I get the difference of all cases (decile 1-10 and decile 1-10), then I sum these differences. If these differences are significantly larger than zero, I can conclude that the CAPM is better than the FF4. The table reports the sum of differences of the CAPM versus fund return (Return), excess return (ExRet), market-adjusted return (ExMkt), the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF). In Panel A, the sums of the differences in the first row are all positive and significant. Also, in the fourth row, the percentage of positive coefficient differences are larger than 50% except for the FF5. It indicates that the CAPM has, conservatively, more than 50% of coefficients that are larger than the coefficients of other models. Furthermore, *t*-statistics and binominal p-values support the significance of my results. For example, the sum of differences of the CAPM versus the Fama-French-Carhart factor model is 1.31 (t=3.6, binominal p-value <1%). To sum up, my first hypothesis is supported by these two tests. The CAPM also dominates other risk models in modelling fund flows in China.

4.5.2 R-squared Decomposition of Flow Prediction with Risk Factors and Non-risk Factors

To address the relative importance of flow determinants in investors' fund selection, I regress fund flows on four groups of flow determinants, including risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics.[18] The dependent variable is fund flow, as defined in Equation 4-1. It measures the rate of asset (fund size) growth in one quarter, which is net of fund returns. The standard errors of coefficients are clustered at both the fund level and the time level. Then, I conduct an R-squared decomposition to find the decomposed R-squared of each determinant. I have the following results from Table 4-6.

$$Flow_{i,t} = \beta_0 + \beta_i^{alpha} * alpha_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + \varepsilon_{i,t}$$

(Eq. 4-6)

[18] Due to the availability of fund holdings data, I remove the group of active investment factors in the flow predictions of the US market. Also, Morningstar ratings and manager tenure do not have enough observations for the China fund sample. I exclude them in the flow predictions of the China market.

Table 4-6 Predictions of Fund Flows with Risk Betas, Alphas and Non-risk Factors

This table shows the prediction for quarterly fund flows with risk-adjusted alphas, risk betas and fund characteristics. The dependent variable is quarterly fund flow. The independent variables include risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics. Risk betas are calculated from the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF) with 24-month/60-month rolling window regressions, while the mispricing-factor model (MF) from Stambaugh and Yuan (2016) is also included for the US market. Active investment factors include fund diversification, industry concentration index, reliance on public information, active share, fund-report attention and return gap. Fundamental fund characteristics include log of fund size, log of fund family size, fund ages, operating ratio, lagged fund flow, prior 12-month return volatility and Morningstar 3-year ratings. Panel A and Panel B show the results of the China sample and the US sample respectively.

$$Flow_{i,t} = \beta_0 + \beta_i^{alpha} * alpha_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + +\varepsilon_{i,t} \quad (4\text{-}6)$$

I run double-clustered regressions to get the coefficients. Decomposed R-squareds (individual R^2) calculated with Shapley-own methods are listed for each regression. I label it as the individual R-squared (Ind. R^2 %) of each independent variable. Regarding the regression, cluster effects are studied with the standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Table 4-6 (continued)

Panel A: China

	(1) CAPM		(2) FF3		(3) FF4		(4) FF5		(5) QF	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
Alpha	2.519***	**10.71**	1.717**	**5.42**	1.328*	**2.82**	1.558**	**3.90**	2.292***	**5.60**
	(3.680)		(2.120)		(1.827)		(2.278)		(2.899)	
Beta MKT	-0.012	1.96	-0.038	1.14	-0.050	2.02	-0.028	0.90	-0.032	0.81
	(-0.253)		(-1.023)		(-1.446)		(-0.780)		(-0.889)	
Beta SMB			0.031	2.33	0.060**	10.95	0.037*	2.76	0.060**	3.93
			(1.303)		(2.248)		(1.862)		(2.570)	
Beta HML			-0.004	0.31	0.025**	4.46	-0.007	0.14		
			(-0.327)		(2.123)		(-0.565)			
Beta UMD					0.005	0.24				
					(0.244)					
Beta CMA							0.028**	4.73		
							(2.356)			
Beta RMW							-0.013	1.42		
							(-0.892)			
Beta I/A									0.000	0.65
									(0.008)	
Beta ROE									0.000	0.96
									(0.005)	
Beta subtotal R^2		**1.96**		**3.79**		**17.67**		**9.96**		**6.35**
Diversification	0.026***	1.98	0.026***	2.12	0.025***	1.72	0.025***	1.91	0.026***	1.92
	(3.659)		(3.838)		(3.536)		(3.607)		(3.472)	
Industry concentration index	0.084	0.96	0.059	0.93	0.070	0.83	0.114	1.11	0.046	0.89
	(0.957)		(0.665)		(0.719)		(1.382)		(0.518)	

Table 4-6 (continued)

Reliance on public information	0.013	1.05	0.015	1.10	0.012	0.92	0.011	0.99	0.016	1.15
	(0.749)		(0.799)		(0.675)		(0.629)		(0.903)	
Fund-report attention	0.033	2.73	0.031	2.61	0.028	2.15	0.027	2.13	0.032	2.70
	(1.458)		(1.364)		(1.360)		(1.312)		(1.444)	
Active share	-0.040	0.18	-0.033	0.17	-0.004	0.14	-0.024	0.14	-0.038	0.18
	(-1.043)		(-0.824)		(-0.109)		(-0.622)		(-1.015)	
Return gap	0.035	0.54	0.040	0.64	0.039	0.55	0.028	0.43	0.031	0.49
	(1.038)		(1.214)		(1.206)		(0.807)		(0.948)	
Active subtotal R^2		**7.45**		**7.56**		**6.32**		**6.71**		**7.32**
Fund size log	-0.030***	21.51	-0.029***	21.31	-0.031***	19.00	-0.030***	21.35	-0.029***	19.89
	(-4.604)		(-4.433)		(-4.597)		(-4.423)		(-4.400)	
Family size log	0.011**	2.22	0.010**	2.20	0.013**	1.94	0.010**	2.14	0.009*	2.05
	(2.120)		(2.093)		(2.393)		(2.035)		(1.830)	
Age (quarter) log	0.008	2.03	0.006	2.14	0.012	1.58	0.008	1.94	0.006	2.17
	(0.707)		(0.510)		(0.915)		(0.665)		(0.568)	
Total operating cost	-0.052	0.17	-0.079	0.17	-0.015	0.14	-0.093	0.16	-0.104	0.16
	(-0.234)		(-0.346)		(-0.068)		(-0.417)		(-0.441)	
Flow	0.145***	41.95	0.150***	44.95	0.146***	38.48	0.150***	43.28	0.147***	43.03
	(3.838)		(3.795)		(3.742)		(3.765)		(3.913)	
Volatility	0.926***	12.01	0.932***	12.46	0.995***	12.06	0.798***	10.56	1.014***	13.42
	(3.682)		(3.975)		(4.190)		(3.602)		(4.297)	
Fundamental subtotal R^2		**79.89**		**83.23**		**73.20**		**79.44**		**80.73**
Intercept	0.083		0.093		0.068		0.127		0.109	
	(0.884)		(1.004)		(0.685)		(1.313)		(1.056)	
Cluster quarter effects	Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes	
Observations	4,686		4,686		4,686		4,686		4,686	
R-squared	0.0577		0.0558		0.0635		0.0578		0.0582	
Adjusted R-squared	0.0549		0.0525		0.0601		0.0542		0.0548	

Table 4-6 (continued)

Panel B: The US

Variables	(1) CAPM		(2) FF3		(3) FF4		(4) FF5		(5) QF		(6) MF	
Alpha	1.952***	**10.33**	2.284***	**9.17**	2.439***	**9.27**	2.019***	**7.36**	1.957***	**7.83**	2.271***	**9.42**
	(5.140)		(5.760)		(6.654)		(5.677)		(5.074)		(5.599)	
Beta MKT	-0.014	0.61	-0.004	0.27	-0.009	0.34	-0.014	0.39	-0.008	0.42	-0.013	0.64
	(-1.260)		(-0.260)		(-0.489)		(-0.922)		(-0.505)		(-0.749)	
Beta SMB			-0.018***	0.44	-0.018***	0.42	-0.016**	0.30	-0.015**	0.28	-0.011	0.18
			(-2.739)		(-2.594)		(-2.395)		(-2.490)		(-1.640)	
Beta HML			0.010*	0.38	0.009	0.39	0.010**	0.44				
			(1.782)		(1.542)		(2.031)					
Beta UMD					-0.005	0.11						
					(-0.822)							
Beta CMA							0.000	0.04				
							(0.132)					
Beta RMW							0.013**	0.45				
							(2.562)					
Beta I/A									-0.000	0.10		
									(-0.001)			
Beta ROE									0.002	0.08		
									(0.486)			
Beta MGMT MF											0.010*	0.31
											(1.898)	
Beta PERF MF											-0.002	0.06
											(-0.229)	
Beta subtotal R^2		**0.61**		**1.09**		**1.26**		**1.63**		**0.88**		**1.19**
Fund size (log)	-0.021***	14.85	-0.021***	15.02	-0.021***	14.67	-0.021***	14.52	-0.021***	14.65	-0.021***	14.80
	(-4.002)		(-3.958)		(-3.933)		(-3.931)		(-3.927)		(-3.930)	

Table 4-6 (continued)

Family size (log)	0.008***	2.56	0.007***	2.46	0.007***	2.43	0.007***	2.41	0.008***	2.49	0.008***	2.48
	(5.507)		(5.100)		(5.075)		(5.117)		(5.126)		(5.206)	
Age (log)	-0.015***	9.55	-0.015***	9.57	-0.015***	9.32	-0.015***	9.49	-0.015***	9.53	-0.015***	9.39
	(-2.721)		(-2.702)		(-2.671)		(-2.701)		(-2.734)		(-2.703)	
Expense ratio	-1.164	0.75	-1.059	0.76	-0.969	0.75	-0.947	0.73	-0.987	0.75	-1.035	0.75
	(-0.593)		(-0.545)		(-0.496)		(-0.486)		(-0.501)		(-0.526)	
Manager tenure (log)	0.004*	0.19	0.004*	0.19	0.004*	0.19	0.005*	0.19	0.005*	0.20	0.004*	0.20
	(1.696)		(1.705)		(1.657)		(1.719)		(1.752)		(1.704)	
Flow	0.304***	45.58	0.303***	45.35	0.308***	45.90	0.312***	46.81	0.311***	47.02	0.307***	45.63
	(19.348)		(19.200)		(18.545)		(17.880)		(18.282)		(18.813)	
Turnover	0.002	0.29	0.003	0.32	0.004	0.35	0.004	0.36	0.003	0.39	0.003	0.35
	(0.471)		(0.641)		(0.724)		(0.732)		(0.730)		(0.698)	
Volatility	0.078	0.10	0.145	0.16	0.197	0.25	0.201	0.24	0.164	0.21	0.161	0.18
	(0.314)		(0.521)		(0.680)		(0.731)		(0.603)		(0.580)	
MS 3-year rating	0.018***	15.18	0.019***	15.89	0.019***	15.61	0.019***	16.26	0.019***	16.06	0.019***	15.60
	(6.655)		(6.437)		(6.716)		(6.822)		(6.535)		(6.783)	
Fundamental subtotal R^2		**89.06**		**89.73**		**89.47**		**91.02**		**91.29**		**89.39**
Intercept	0.268**		0.262**		0.260**		0.261**		0.257**		0.266**	
	(2.308)		(2.185)		(2.138)		(2.172)		(2.146)		(2.169)	
Cluster quarter effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	123,629		122,473		122,297		122,526		122,094		122,661	
R-squared	0.0071		0.0072		0.0074		0.0074		0.0073		0.0073	
Adjusted R-squared	0.00704		0.00706		0.00725		0.00726		0.00715		0.00722	

For the China fund market, first, consistent with the results in the previous section, CAPM alpha significantly predicts fund flows. Its coefficient is positive and significant at 1% level (2.519, t=3.68) and it contributes to a large proportion of R-squared (10.71%). Also, risk-adjusted alphas show positive and significant coefficients ranging from 1.558 (t=2.278) under the FF5 model to 2.519 (t=3.68) under the CAPM. Second, market beta itself has little explanatory power for fund flows. The risk parameters that affect fund flows are the risk loadings of size factor (SMB), value factor (HML) and investment factor (CMA). SMB risk and HML risk show significant and positive coefficients of 0.06 (t=2.248) and 0.025 (t=2.123) under the FF4 model. CMA risk also has a positive and significant coefficient of 0.028 (t=2.356) under the FF5 model. This suggests that Chinese investors potentially actively seek positive exposure to small size premium, value premium, and investment growth premium. Especially, the risk factors from the FF4 model provide a large explanatory power (17.67%) for fund flows compared to other determinants. Third, among active investment measures, large fund diversification attracts more fund flows, and this is consistent across all risk model regressions. Fund diversification has positive and significant coefficients, ranging from 0.025 (t=3.536) under the FF4 model to 0.026 (t=3.838) under the FF3 model. However, the contribution of the group of active investment factors to fund flows is low, ranging from 6.32% to 7.56%. Finally, consistent with the second hypothesis (H2), I find evidence that the non-risk factors of fundamental fund characteristics significantly affect future fund flows with relatively large explanatory power ranging from 73.2% to 83.23%.

Within fundamental fund characteristics, first, the strongest predictor is lagged fund flow. It has positive and significant coefficients at the 1% level, ranging from

0.145 (t=3.838) under the CAPM to 0.150 (t=3.765) under the FF5 model. Also, lagged flow has its decomposed R-squared ranging from 38.48% to 44.95%. This is consistent with previous literature showing that investors are aware of the smart money effect (Gruber, 1996; Zheng, 1999; Kewani and Stolin, 2008). Second, fund size has the second largest explanatory power for fund flows, with decomposed R-squared ranging from 19% to 21.51%. It also shows negative and significant coefficients at the 1% level ranging from -0.029 (t=-4.433) under the FF3 model to -0.031 (t=-4.597) under the FF4 model. It suggests that small funds tend to attract higher money inflows, which is consistent with the literature on the scale-decreasing return, which holds that fund size is negatively related to fund performance (Chen et al., 2004; Yan, 2008; Pollet and Wilson, 2008). Third, I find some evidence that investors tend to choose funds with a larger family size and higher past volatility. Fund family size has positive and significant coefficients ranging 0.009 (t=1.83) at the 10% level under the Q-factor model to 0.013 (t=2.393) at the 5% level under the FF4 model. Also, past volatility has positive and significant coefficients at the 1% level, ranging from 0.798 (t=3.602) under the FF5 model to 1.014 (t=4.297) under the Q-factor model. It implies that a larger fund family size indicates better performance (Bhojraj, Cho and Yehuda, 2011) and high past volatility might reduce funds' participation costs. Overall, the findings confirm that non-risk factor plays a critical role in directing mutual fund flows in China.

For the US market, first, I find that investors tend to pick funds with a smaller size, higher lagged flow and higher Morningstar rating. Specifically, in Column 3 Panel B, based on the FF4 model, fund size is significantly and negatively related to fund flows at the 1% level (-0.021, t=3.933, R^2=14.67%), which implies that investors are sensitive to scale-decreasing return (Chen et al., 2004). It shows explanatory power ranging from

14.52% to 15.02%. In addition, lagged fund flow has a positive and significant coefficient at the 1% level (0.308, t=18.545, R^2=45.9%) with decomposed R-squared ranging from 45.58% to 47.02%. It implies that investors might be aware of the smart money effect (Gruber, 1996; Zheng, 1999). Moreover, Morningstar 3-year ratings also positively drive fund flows (0.019, t=6.716, R^2=15.61%) with explanatory power ranging from 15.18% to 16.26%. This suggests that the rating effect also exists and drives fund flows in the US market (Guercio and Tkac, 2008; Nanda, Wang and Zheng, 2004).

Second, consistent with my Hypothesis Two, the fundamental fund characteristics group has the most substantial R-squared, greater than those of the alpha group and the beta group, ranging from 89.06% to 91.29%. Third, I find a significant positive relation between fund flow and risk-adjusted alpha. All of risk-adjusted alphas show positive and significant coefficients. For instance, CAPM alpha has a coefficient of 1.952 (t=5.140), which is significant at the 1% level. Risk-adjusted alphas offer explanatory power for fund flow, ranging from 7.36% to 10.33%. CAPM alpha has a large explanatory (10.33%) power for fund flows. Consistent with Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016), it confirms the power of CAPM in directing fund flows in the US. Fourth, the subtotal R-squared of risk beta is relatively smaller than the R-squared of risk-adjusted alphas. It shows decomposed R-squared ranging from 0.61% to 1.63%. In Column 2, the subgroup R-squared (1.09%) of market risk factor, size factor and value factor is less than alpha R-squared (9.17%). Also, in terms of coefficients, SMB risk shows negative and significant coefficients -0.018 (t=-2.739) at the 1% level under the FF3 model. HML risk shows positive and significant coefficients of 0.01 (t=1.782) at the 10% level under the FF3 model and 0.01 (t=2.031) at the 5% level under the FF5 model. In addition, RMW risk shows a positive and significant coefficient of 0.013 (t=2.562) at the 1% level under the FF5 model and MGMT risk shows a positive and significant coefficient of 0.01 (t=1.898) at the 10% level under the Q-factor model. Taken together, the results suggest that investors seem to have some concerns over risk beta, but they attach more weight to risk-adjusted alpha. Overall, the non-risk factors of fundamental fund characteristics have the largest explanatory power for fund flows in the US market.

To conclude, from the perspective of fundamental fund characteristics, I find that non-risk factors have the largest explanatory power for future fund flows in both the China and US mutual fund market. Chinese investors tend to choose small funds with high lagged flow and high past volatility, while US investors prefer funds with small size, high lagged flow and a high Morningstar rating. Under the CAPM specification in China, lagged fund flow (41.95%), fund size (21.51%) and return volatility (12.01%) account for the top determinants with relatively high explanatory power. While for US funds, lagged fund flow (45.58%), fund size (14.85%) and Morningstar rating (15.18%) are the top non-risk factors explaining fund flows.

The empirical results imply that, first, scale-decreasing return (Chen et al., 2004; Pollet and Wilson, 2008) plays an essential role in affecting investors' fund decisions. As the size grows, funds may suffer from a liquidity problem, or they may fail to scale up their investment opportunities. Second, the smart money effect might be well recognized by investors as they follow funds with higher lagged flows to obtain greater future performance (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). Third, US investors might be more risk-averse while Chinese investors might be relatively risk-seeking and select funds with large past volatility.

From the perspective of risk-adjusted alpha, CAPM alpha has a large R-squared in both China (10.71%) and the US (10.33%). It also has coefficients of 2.519 (t=3.680) in China and 1.952 (t=5.14) in the US, which are significant at the 1% level. This implies the power of CAPM in directing fund flows in both the China and US markets.

From the perspective of risk factors, first, consistent with Barber, Huang and Odean (2016) and Agarwal, Green and Ren (2018), the result indicates that investors may pool factor-related returns with alpha values, which results in relatively lower explanatory power for the risk beta group. Second, with relative lower explanatory power, the SMB risk factor significantly and positively predicts fund flows in China, while the sign of its coefficient reverses in the US market. This indicates that investors are sensitive to size premiums in their fund investments. Chinese investors tend to purchase funds with a high-risk loading on size factor. However, US investors are risk-averse and not willing to be exposed to it. Third, value risk (HML) and investment risk (CMA) also positively predict flows in China. Also, value risk (HML), profitability risk (RMW) and management risk (MGMT) positively attract flows in the US. It suggests that Chinese investors have an incentive to chase value and investment premiums and US investors tend to tilt their fund portfolios to chase value, profitability and management premiums. However, these risk factors, including size, value, investment and profitability, can only explain a small portion of fund flows.

4.5.3 Long-Term Fund Flow Determinants

To test Extended Hypothesis Two regarding the impact of flow determinants over different horizons, I extend the analysis and take average cumulative fund flows over one-year, two-year and three-year horizons as dependent variables. I run the regression as follows:[19]

$$cumulative\ flow_{i,t} = \beta_0 + \beta_i^{alpha} * alpha_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t} + \sum \beta_i^{active} * active\ factor_{i,t} + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + \varepsilon_{i,t}$$

(Eq. 4-7)

Table 4-7 Long-Term Predictions of Fund Flows with Risk Betas, Alphas and Non-risk Factors for CAPM

This table shows predictions of fund flows over one-year, two-year and three-year horizons with risk-adjusted alpha, risk factors, active investment factors and fund characteristics. The dependent variable is average cumulative flow. Risk-adjusted alphas and risk betas are calculated from the CAPM with 24-month/60-month rolling window regressions. Active investment factors include fund diversification, industry concentration index, reliance on public information, fund-report attention, active share and return gap. Fundamental fund characteristics include log of fund size, log of fund family size, fund ages, operating ratio, lagged fund flow, prior 12-month return volatility and Morningstar rating. Panel A and Panel B show the results of the China sample and the US sample respectively.

$$cumulative\ flow_{i,t} = \beta_0 + \beta_i^{alpha} * alpha_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + \varepsilon_{i,t} \quad (4\text{-}7)$$

Decomposed R-squareds (Individual R^2 %) calculated with Shapley-own methods are listed for each regression. Regarding the regression, cluster effects are studied with standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

[19] Due to the availability of fund holdings data, I remove the active investment factor group in the long-term flow predictions of the US market. Also, Morningstar ratings and manager tenure do not have enough observations for the China fund sample. I exclude them in the long-term flow predictions of the China market.

Table 4-7 (continued)

Panel A: China

	(1) Year one		(2) Year two		(3) Year three	
Variables	Coeff.	Ind. R^2	Coeff.	Ind. R^2	Coeff.	Ind. R^2
CAPM alpha	1.872***	**14.07**	1.402***	**12.27**	1.559***	**14.01**
	(3.423)		(3.737)		(4.851)	
Beta MKT CAPM	-0.040	**0.89**	-0.049*	**3.05**	-0.037*	**1.98**
	(-1.379)		(-1.840)		(-1.678)	
Diversification	0.018***	1.45	0.016**	1.99	0.014***	2.18
	(2.794)		(2.409)		(2.627)	
Industry concentration index	0.331***	6.17	0.258***	5.78	0.180***	3.05
	(3.088)		(3.344)		(2.620)	
Reliance on public information	0.020	3.32	0.014	3.98	0.016	4.58
	(1.269)		(1.034)		(1.531)	
Fund-report attention	-0.006	0.63	-0.007	1.40	-0.007	1.87
	(-0.524)		(-0.982)		(-1.579)	
Active share	-0.028	0.92	-0.026	1.08	-0.017	0.96
	(-1.013)		(-1.072)		(-0.711)	
Return gap	0.103**	8.94	0.045	2.27	0.006	0.60
	(1.988)		(1.588)		(0.310)	
Active subtotal R^2		**21.44**		**16.51**		**13.24**
Fund size log	-0.024***	19.92	-0.023***	34.89	-0.024***	45.07
	(-3.816)		(-4.041)		(-4.665)	
Family size log	0.008*	2.04	0.011**	3.90	0.013***	5.16
	(1.813)		(2.155)		(2.688)	
Age (quarter) log	0.009*	2.15	-0.000	8.34	0.005	4.98
	(1.713)		(-0.071)		(0.928)	
Total operating cost	-0.140	0.18	-0.146	0.37	-0.057	0.39
	(-0.812)		(-0.944)		(-0.444)	
Flow	0.134***	31.02	0.057***	9.64	0.024*	2.30
	(2.943)		(3.150)		(1.727)	
Volatility	0.793**	8.29	0.685***	11.03	0.699***	12.88
	(2.568)		(3.646)		(4.773)	
Fundamental subtotal R^2		**63.60**		**68.17**		**70.77**
Intercept	0.206**		0.166**		0.141**	
	(2.237)		(2.227)		(1.968)	
Cluster quarter effects	Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes	
Observations	3,060		3,060		3,060	
R-squared	0.1378		0.1430		0.1854	
Adjusted R-squared	0.134		0.139		0.182	

Table 4-7 (continued)

Panel B: The US

	(1) Year one		(2) Year two		(3) Year three	
Variables	Coeff.	Ind. R^2	Coeff.	Ind. R^2	Coeff.	Ind. R^2
Fund size (log)	-4.133	16.37	-3.391	11.16	-2.268	11.21
	(-1.032)		(-1.036)		(-1.040)	
Family size (log)	3.314	11.47	3.129	9.84	2.088	9.85
	(1.021)		(1.023)		(1.024)	
Age (log)	-12.443	36.13	-14.232	41.12	-9.492	41.13
	(-1.004)		(-1.005)		(-1.005)	
Expense ratio	414.768	3.04	452.690	2.27	301.385	2.26
	(0.980)		(0.979)		(0.977)	
Manager tenure (log)	-0.657	1.29	-0.854	1.24	-0.570	1.24
	(-0.805)		(-0.836)		(-0.837)	
Flow	-51.219	18.47	-50.286	15.09	-33.541	15.08
	(-1.021)		(-1.011)		(-1.012)	
Turnover	-8.363	8.07	-8.724	8.61	-5.811	8.58
	(-1.000)		(-1.000)		(-0.999)	
Volatility	-142.324	2.51	-255.539	8.64	-170.405	8.63
	(-1.039)		(-1.055)		(-1.055)	
Morningstar 3-year rating	-1.413	2.06	0.355	0.28	0.241	0.28
	(-0.976)		(0.672)		(0.685)	
CAPM alpha	109.911	0.57	-107.151	1.13	-71.629	1.13
	(0.860)		(-0.613)		(-0.615)	
Beta MKT CAPM	1.129	0.02	6.485	0.62	4.317	0.62
	(0.550)		(1.122)		(1.121)	
Intercept	72.453		63.356		42.350	
	(1.014)		(1.018)		(1.021)	
Cluster quarter effects	Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes	
Observations	117,176		117,176		117,176	
R-squared	0.0001		0.0003		0.0003	
Adjusted R-squared	0.0000535		0.000235		0.000235	

Table 4-7 reports the results for CAPM since it is dominant in directing fund flow in both markets.[20]

For the China market, first, the subtotal R-squared of fundamental fund characteristics increases monotonically over one-year to three-year horizons. This suggests that cross-sectional variables capture fundamental characteristics that are relatively more relevant to explain the distribution of fund flows in the long run. Second, it shows that CAPM alpha has higher explanatory power for one-year flows (14.07%) and three-year flows (14.01%) than for quarterly flows (10.71%) in Table 4-6. Especially, its explanatory power reaches its peak for a one-year flow. Also, the coefficient of CAPM alpha has the largest coefficient of 1.872 (t=3.423) over a one-year horizon and then decays over two- and three-year horizons. In addition, the non-risk factor group makes the highest R-squared contribution and increases over time. It has an explanatory power of 63.60% for one-year flows and of 70.77% for three-year flows. Fundamental fund characteristics persistently affect investors' decisions over all horizons. Especially, fund size, return volatility and fund family size show an increasing explanatory power for fund flows over time. The active investment group's explanatory power decreases from 21.44% over a one-year horizon to 13.24% over a three-year horizon. Also, fund diversification and industry concentration show a decay on their coefficients over one-year to three-year horizons. It indicates that investors would rely on active measures in the short term while fundamental characteristics play an increasing role in determining fund flows in the long term.

[20] Main results in the long-term flow predictions for other risk models used in Table 4-6 Panel A are similar.

For the US market, I find that fundamental fund characteristics are insignificant to explain long-term fund flows. In Column 3 of Table 4-7 Panel B, fund size is negatively related but insignificant to future fund flows at the 5% level (-4.133, t=-1.032, R-squared=16.37%). Past flows and Morningstar ratings show negative and insignificant coefficients at the 5% level. Some US funds report their total net assets monthly. This enables investors to analyze fund flows on a monthly basis. While funds disclose their size quarterly or biannually in China, investors might be more sensitive to relatively short-term flow determinants due to fund disclosures in the US. The results show that relatively high-frequency flows (monthly) might only be forecastable in the short term, within one year. Consistent with Bollen and Busse (2005), short-term performance on a quarterly basis might be predictable, while in the long-run there is little persistence.

Overall, the results indicate that flow determinants in the US market might only have predictive power in the short term (within one year), while in China fundamental fund characteristics have long-term (one to three years) predictive power for fund flows. Over a long horizon, investors in China are more sensitive to fund size, return volatility and fund family size. Funds with the larger size, lower return volatility or in a smaller fund family trigger money outflows. Also, they rely less on active measures in the longer term. Overall, consistent with Extended Hypothesis Two, non-risk factors are more reliable for investors and their fund decisions in the long term.

4.5.4 Test of the Non-risk Attribution to CAPM's Success

$$Flow_{i,t} = \beta_0 + \beta_i^{alpha} * CAPM\ alpha_{i,t-1} + \beta_i^{risk} * CAPM\ beta_{i,t-1} + \beta_i^{alpha-beta} * CAPM\ alpha_{i,t-1} * CAPM\ beta_{i,t-1} + \sum \beta_i^{nonrisk} * nonrisk\ factor_{i,t-1} + \sum \beta_i^{nonrisk-alpha} * nonrisk\ factor_{i,t-1} * CAPM\ alpha_{i,t-1} + \varepsilon_{i,t}$$

(Eq. 4-8)

Table 4-8 Test Flow-Performance Sensitivity with Non-risk Factors

This table shows predictions for fund flows with CAPM alphas and interaction terms between CAPM alphas and non-risk factors. The dependent variable is the quarterly fund flow. The independent variables include risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics. Risk-adjusted alphas and risk betas are calculated from CAPM with 24-month/60-month rolling window regressions. Active investment factors include fund diversification, industry concentration index, reliance on public information, active share, fund-report attention and return gap. Panel A and Panel B show the results for the China sample and the US sample respectively. I run double-clustered regressions to get the coefficients. Fundamental fund characteristics include log of fund size, log of fund family size, fund age, total expense ratio, lagged fund flow, prior 12-month return volatility and Morningstar 3-year rating. Decomposed R-squareds calculated with Shapley-own methods are listed for the regression. They include individual R^2 (%) and group R^2 (%). Regarding the regression, cluster effects are studied with standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: China

Variables	**Coeff.**	***t*-statistics**	**Ind. R^2**	**Group R^2**
CAPM alpha	36.758***	(3.049)	4.51	**4.51**
Beta MKT CAPM	-0.016	(-0.376)	2.16	**2.16**
Fund size (log)	-0.030***	(-3.958)	18.17	**63.80**
Family size (log)	0.014**	(2.265)	1.92	
Age (quarter) log	0.005	(0.519)	1.72	
Total expense ratio	-0.072	(-0.287)	0.14	
Flow	0.130***	(3.434)	30.52	
Volatility	1.006***	(4.264)	11.33	
Diversification	0.023***	(4.163)	1.43	**6.36**
Industry concentration index	0.136**	(1.983)	0.93	
Reliance on public information	0.012	(0.690)	0.84	
Fund-report attention	0.039*	(1.912)	2.68	
Active share	-0.031	(-0.728)	0.13	
Return gap	0.028	(0.816)	0.34	
CAPM alpha*Beta MKT CAPM	3.087	(1.025)	0.83	**0.83**
CAPM alpha*Fund size	-0.717	(-1.368)	2.64	**15.97**
CAPM alpha*Family size	-1.151	(-1.547)	2.01	
CAPM alpha*Age	-0.030	(-0.064)	0.60	
CAPM alpha*Expense	21.296	(0.523)	1.02	
CAPM alpha*Flow	3.470	(1.207)	8.31	
CAPM alpha*Volatility	-36.330**	(-2.223)	1.40	
CAPM alpha*Diversification	2.224**	(2.344)	2.87	**6.37**
CAPM alpha*Industry concentration index	-11.897*	(-1.662)	0.61	
CAPM alpha*Reliance on public information	-0.100	(-0.059)	0.27	

Table 4-8 (continued)

CAPM alpha*Fund report attention	-0.752	(-0.503)	1.35	
CAPM alpha*Active share	-4.564	(-0.655)	0.64	
CAPM alpha*Return gap	5.772**	(2.044)	0.64	
Intercept	-0.014	(-0.138)		
Cluster quarter effects	Yes			
Cluster fund effects	Yes			
Observations	4,686			
R-squared	0.0660			
Adjusted R-squared	0.0606			

Panel B: The US

Variables	Coeff.	*t*-statistics	Ind. R^2	Group R^2
CAPM alpha	20.079***	(3.009)	7.06	**7.06**
Beta MKT CAPM	-0.012	(-1.126)	0.47	**0.47**
Fund size (log)	-0.021***	(-4.045)	14.48	**79.40**
Family size (log)	0.008***	(5.673)	2.50	
Age(log)	-0.015***	(-2.688)	8.95	
Expense ratio	-1.246	(-0.629)	0.72	
Manager tenure (log)	0.004*	(1.679)	0.17	
Flow	0.285***	(19.378)	39.10	
Turnover	0.002	(0.353)	0.26	
Volatility	0.050	(0.189)	0.08	
MS 3-year rating	0.018***	(6.499)	13.15	
CAPM alpha*Beta MKT CAPM	-0.260	(-0.253)	0.65	**0.65**
CAPM alpha*Fund size (log)	-0.735**	(-2.305)	1.23	**12.42**
CAPM alpha*Family size (log)	-0.073	(-0.569)	0.91	
CAPM alpha*Age (log)	-0.487	(-1.116)	0.84	
CAPM alpha*Expense ratio	-77.541	(-0.707)	0.87	
CAPM alpha*Manager tenure (log)	0.096	(0.399)	0.76	
CAPM alpha*Flow	5.963***	(3.335)	5.26	
CAPM alpha*Turnover	-0.031	(-0.081)	0.52	
CAPM alpha*Volatility	-5.944	(-0.445)	0.60	
CAPM alpha*MS 3-year rating	0.377	(1.208)	1.42	
Intercept	0.268**	(2.300)		
	(2.300)			
Cluster quarter effects	Yes			
Cluster fund effects	Yes			
Observations	123,629			
R-squared	0.0073			
Adjusted R-squared	0.00716			

To find out whether the dominance of CAPM is attributable to non-risk factors, in this section, I empirically regress fund flows on CAPM alpha and the interaction term between CAPM alpha and non-risk flow determinants.[21] The dependent variable is the fund flow. It measures the rate of growth in net assets (fund size) in one quarter, which is net of fund returns. Utilizing the interaction term, I find how active investment factors and fundamental fund characteristics affect alpha-flow sensitivity.

For the China market, by looking at the first column in Table 4-8 Panel A, I find that CAPM alpha has a positive coefficient of 36.758 (t=3.049, R^2= 4.51%). Considering the size of coefficient, it might be offset by the coefficient of the interaction term of CAPM alpha and past volatility (-36.33, t=-2.223). The fundamental fund characteristics group still offers the highest explanatory power for fund flows of 63.8%. In addition, the interaction group of active skills has an explanatory power of 6.37%, while the interaction group's fundamental fund characteristics have explanatory power of 14.58%. Moreover, 1% increase of the interaction term of fund diversification and return gap can enhance alpha-driven flows by 2.224% (t=2.234, R^2=2.87%) and 5.772% (t=2.044, R^2=0.64%) respectively. However, past volatility has a negative effect on CAPM alpha in driving fund flows. Interestingly, past volatility has a positive coefficient to drive fund flow; it might be attributable to investors' preference for funds with flexible trading strategies (Guo, 2016) since flexible investment ideas result in high past volatility. It implies that there is a trade-off between increasing return volatility and attracting money flows.

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[21] Due to the availability of fund holdings data, I remove the active investment factor group in the interaction regressions of the US market. Also, Morningstar ratings and manager tenure do not have enough observations for the China fund sample. I exclude them in the interaction regressions of the China market.

The result implies that CAPM alpha outperforms other risk models in driving flows through the interaction effect with fund diversification and return gap. These regression results support non-risk factors also affecting investors' decisions to utilize a risk model. It suggests that the success of CAPM might be attributable to its ability to handle fund liquidity and scale-decreasing return (Chen et al., 2004; Pollet and Wilson, 2008) proxied by fund diversification. It might also be attributed to the active investment skill of possessing advantage information, proxied by return gap (Kacperczyk, Sialm and Zheng, 2008). It reflects the ability to bring investors hidden profits or cover other costs efficiently. A well-performing fund with high CAPM alpha tends to enjoy greater fund flows with greater fund diversification and a larger return gap.

For the US market, in Panel B, it shows that lagged flow, fund size and the Morningstar rating still have the top three decomposed R-squared values (39.10%, 14.48% and 13.15%) which are higher than that of CAPM alpha (7.06%). The interaction term between CAPM alpha and fund size is significantly negative for fund flow (-0.735, t=-2.305, R^2=1.23%), while the interaction term between CAPM alpha and lagged flow is positively related to fund flow (5.963, t=3.335, R^2=5.26%). It suggests that the ability of CAPM alpha to attract money flows is enhanced by lagged fund flow, but it is negatively affected by fund size. For funds with CAPM alpha at a similar level, US investors tend to choose a small one with higher lagged flow. This is consistent with the scale-decreasing return from Chen et al. (2004) and the smart money effect from Gruber (1996). Concerns over whether fund managers have the ability to scale up their investment ideas, find alternative opportunities (Pollet and Wilson, 2008) and deal with the organizational diseconomies (Chen et al., 2004) can affect investors' fund decisions. In addition, investors are aware of the funds held by smart investors, since funds with higher money flows subsequently outperform their peers with lower flows (Zheng, 1999).

Overall, the fundamental fund characteristics group still offers the highest explanatory power for future fund flows in China (63.8%) and the US (79.4%), when the interaction terms between CAPM alpha and non-risk factors are added. In China, the ability of CAPM alpha to drive fund flows is strengthened by fund diversification and return gap but weakened by the past volatility. For funds with attractive CAPM alphas, Chinese investors prefer funds with higher diversification and higher return gaps. It indicates that skills in managing scale-decreasing return with diversification (Pollet and Wilson, 2008) and abilities to utilize advantage information (Kacperczyk, Sialm and Zheng, 2008) and deal with hidden expenses such as fees from brokers or other transaction costs both contribute to the success of CAPM alpha. In the US, the ability of CAPM alpha is enhanced by lagged fund flow and weakened by fund size. For funds with superior CAPM alpha, US investors are more willing to purchase small funds and funds receiving higher lagged flows. This implies that scale-decreasing return (Chen et al., 2004) and the smart money effect (Gruber, 1996; Zheng, 1999) are primary factors affecting the success of CAPM alpha in directing money flows in the US.

4.6. Robustness Test

To check the robustness of my results, I conduct further tests. Section 4.6.1 discusses the impact of investor sophistication on flow determinants. Section 4.6.2 studies how scale-decreasing return affects flow determinants. Section 4.6.3 analyses how participation costs affect flow determinants.[22]

The robustness tests confirm my findings that non-risk factors outperform risk-factors and risk-adjusted alphas in attracting fund flows, even after controlling for investor sophistication, scale-decreasing returns and participation costs. In addition, it also indicates that sophisticated investors utilize advanced methods in their fund selection (Barber, Huang and Odean, 2016).

4.6.1 Investor Sophistication and Flow Determinants

[22] Due to the availability of fund holdings data, I remove the group of active investment factors in the robustness test of the US market. Also, Morningstar ratings and manager tenure do not have enough observations for the China fund sample. I exclude them in the robustness test of the China market.

Table 4-9 Investor Sophistication and Flow Determinants

This table shows predictions of quarterly fund flows with fundamental fund characteristics, CAPM alpha, market beta and their interaction term with a dummy variable that proxies for investor sophistication following Barber, Huang and Odean (2016). The dummy variable differentiates investor sophistication from broker-sold or direct-sold channels, institutional funds or retail funds, and a high sentiment period or low sentiment period, and young or old funds. The independent variables include risk-adjusted alpha, risk beta, active investment factor and fundamental fund characteristics. Risk-adjusted alphas and risk betas are calculated from the CAPM with 24-month/60-month rolling window regressions. Fundamental fund characteristics include log of fund size, log of fund family size, fund age, total expense ratio, log of manager tenure, lagged fund flow, annual turnover, prior 12-month return volatility, and Morningstar 3-year rating. Active investment factors include fund diversification, industry concentration index (ICI), reliance on public information (RPI), fund-report attention, active share and return gap. I run double-clustered regressions to get the coefficients. Decomposed R-squareds (individual R^2 %) calculated using Shapley-own methods are listed for each regression. Regarding the regression, cluster effects are studied with standard errors clustered at both fund level and the quarter level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: China

	(1) Institutional funds		(2) Retail funds		(3) High sentiment		(4) Low sentiment		(5) Old funds		(6) Young funds	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
CAPM alpha	2.635***	**11.08**	2.469***	**10.04**	2.065**	13.25	1.975***	5.63	1.420*	**2.26**	3.182***	**15.47**
	(3.956)		(3.498)		(2.202)		(3.981)		(1.755)		(2.924)	
CAPM beta	-0.003	**0.77**	-0.013	**1.86**	-0.097*	5.91	-0.167**	5.26	0.022	**1.49**	-0.031	**2.99**
	(-0.065)		(-0.270)		(-1.845)		(-2.068)		(0.435)		(-0.429)	
Fund size	-0.032***	17.14	-0.031***	21.78	-0.022***	10.66	-0.035***	23.47	-0.025***	12.43	-0.041***	19.23
	(-4.422)		(-4.561)		(-3.289)		(-5.083)		(-3.329)		(-4.524)	
Family size	0.016***	6.67	0.010*	2.91	0.013**	5.54	0.023**	11.86	0.009	5.60	0.028***	10.23
	(3.317)		(1.892)		(2.290)		(2.302)		(1.496)		(3.622)	
Age	0.013	1.44	0.008	2.16	0.031**	7.76	0.008	0.98	0.008	2.77	-0.003	0.79
	(1.279)		(0.714)		(2.334)		(0.678)		(0.503)		(-0.167)	
Expense	0.106	0.51	-0.073	0.13	-0.061	0.71	0.229	2.51	-0.154	0.59	0.432	1.11
	(0.533)		(-0.340)		(-0.205)		(0.979)		(-1.063)		(0.783)	

Table 4-9 (continued)

Flow	0.149***	43.42	0.146***	41.43	0.132**	32.29	0.092	11.04	0.237**	51.71	0.110***	27.66
	(3.986)		(3.851)		(2.003)		(.)		(2.541)		(4.055)	
Volatility	0.874***	9.60	0.952***	12.49	0.891***	11.95	1.169***	10.97	0.763*	8.02	1.150***	11.81
	(3.218)		(3.688)		(3.096)		(2.973)		(1.797)		(4.392)	
Fundamental subtotal R^2		**78.78**		**80.90**		**68.91**		**60.82**		**81.13**		**70.83**
Diversification	0.029***	2.57	0.025***	1.82	0.019**	3.31	0.051***	8.97	0.016*	4.24	0.033***	4.36
	(3.028)		(3.823)		(2.000)		(3.876)		(1.933)		(2.859)	
ICI	0.105	0.98	0.082	0.88	-0.029	0.52	0.535***	13.16	0.421**	3.78	-0.093	0.43
	(1.089)		(0.949)		(-0.249)		(5.179)		(2.534)		(-1.385)	
RPI	0.027	1.47	0.013	0.95	0.022	2.14	0.035**	3.12	0.019	0.18	0.010	1.08
	(1.205)		(0.733)		(0.860)		(2.222)		(1.633)		(0.385)	
Fund-report attention	0.038*	3.43	0.034	2.88	0.023	2.34	0.010	1.37	0.046	6.33	0.023*	1.83
	(1.697)		(1.527)		(1.566)		(0.433)		(1.532)		(1.679)	
Active Share	-0.030	0.16	-0.040	0.17	-0.049	1.00	-0.046	0.59	0.007	0.46	-0.100*	1.51
	(-0.657)		(-1.022)		(-0.904)		(-0.515)		(0.165)		(-1.660)	
Return Gap	0.041	0.76	0.034	0.49	0.078	2.61	0.032	1.09	0.004	0.12	0.067	1.49
	(1.168)		(0.998)		(1.570)		(1.523)		(0.123)		(1.417)	
Active subtotal R^2		**9.37**		**7.20**		**11.93**		**28.29**		**15.12**		**10.71**
Intercept	-0.047**		0.095		-0.050***		-0.045***		-0.028***		-0.052***	
	(-2.474)		(1.217)		(-3.518)		(-4.024)		(-3.086)		(-3.587)	
Cluster quarter effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	4,678		4,688		4688		4688		4,688		4,688	
R-squared	0.0531		0.0584		0.0136		0.0080		0.0362		0.0340	
Adjusted R-squared	0.0503		0.0556		0.0107		0.00499		0.0334		0.0312	

Table 4-9 (continued)

Panel B: The US

	(1) Broker-sold funds		(2) Direct-sold funds		(3) Institutional funds		(4) Retail funds		(5) High sentiment		(6) Low sentiment	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
CAPM alpha	1.465***	**10.74**	1.693***	**10.29**	3.575*	**18.00**	1.427***	**9.71**	0.551	**8.03**	1.310**	**6.53**
	(3.295)		(3.958)		(1.813)		(4.442)		(0.603)		(2.505)	
CAPM beta mkt	-0.000	**0.52**	-0.012	**0.17**	0.003	**0.22**	-0.010	**0.47**	-0.010	**4.33**	0.002	**4.16**
	(-0.025)		(-0.999)		(0.275)		(-0.990)		(-0.436)		(0.095)	
Fund size	-0.014***	7.25	-0.014***	7.84	-0.009***	4.63	-0.014***	8.47	-0.014***	5.03	-0.011***	6.96
	(-5.283)		(-4.009)		(-2.732)		(-6.470)		(-4.244)		(-5.627)	
Family size	0.009***	5.31	0.010***	6.72	0.006**	3.51	0.010***	6.14	0.007***	3.45	0.006***	4.26
	(5.152)		(2.676)		(2.149)		(4.105)		(4.088)		(5.439)	
Age	-0.005	4.11	-0.018***	8.28	-0.019***	5.87	-0.012**	7.28	-0.000	2.44	-0.013***	6.63
	(-1.595)		(-2.791)		(-4.379)		(-2.372)		(-0.136)		(-4.180)	
Expense	0.006**	0.70	0.008	0.86	0.002	0.46	0.007*	0.73	0.005*	1.04	0.003**	0.81
	(2.561)		(1.291)		(0.680)		(1.793)		(1.908)		(2.464)	
Tenure	1.205***	1.61	0.142	0.68	1.993	3.35	0.478	0.52	2.982***	6.09	1.803***	2.76
	(3.038)		(0.072)		(1.032)		(0.382)		(3.522)		(3.589)	
Flow	0.322***	51.24	0.294***	46.76	0.270***	41.84	0.309***	49.67	0.317***	54.79	0.312***	43.55
	(14.447)		(15.547)		(8.780)		(17.566)		(8.758)		(8.280)	
Turnover	-0.000	0.17	0.007	0.90	-0.005	0.19	0.005	0.63	-0.012***	0.75	-0.007***	0.58
	(-0.085)		(0.868)		(-0.654)		(0.814)		(-3.438)		(-3.512)	
Volatility	-0.314**	0.90	0.419	1.38	-0.151	0.63	0.161	0.35	0.289	1.40	-0.166	1.32
	(-2.353)		(0.955)		(-0.842)		(0.537)		(1.121)		(-0.453)	
MS 3-year raing	0.022***	17.45	0.022***	16.12	0.027***	21.29	0.020***	16.02	0.023***	12.66	0.025***	22.45
	(8.756)		(11.972)		(6.030)		(11.450)		(5.096)		(9.611)	
Fundamental subtotal R^2		**88.74**		**89.55**		**81.78**		**89.82**		**87.65**		**89.32**
Intercept	0.026***		0.022***		0.023***		0.038***		0.011*		0.039***	
	(5.651)		(6.151)		(6.318)		(5.511)		(1.735)		(6.328)	
Cluster quarter effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	123,537		123,537		123,629		123,629		31302		31302	
R-squared	0.0026		0.0042		0.0009		0.0059		0.0359		0.0536	
Adjusted R-squared	0.00252		0.00416		0.000811		0.00582		0.0356		0.0532	

Regarding the Chinese market, in this section, I test my results under different investor sophistication. I differentiate investor sophistication in three ways: institutional fund versus retail fund, high investor sentiment period versus low investor sentiment period, and old fund versus young fund.[23]

I identify a fund as an institutional fund if its institutional holdings are over 50%. Similarly, a retail fund has over 50% of its shares held by retail investors. From Table 4-9 Panel A Columns 1 and 2, in institutional funds, fundamental fund characteristics and active measures show R-squareds of 78.78% and 9.37% respectively. Their sum of R-squared (88.15%) is larger than the R-squared of CAPM alpha (11.08%). In retail funds, fundamental fund characteristics and active measures have R-squareds of 80.90% and 7.20% respectively. Their sum of R-squared is also larger than the R-squared of CAPM alpha (10.04%). It is consistent with the results in Table 4-6 as investors show more concerns over non-risk factors than risk-adjusted alphas under different types of investor in China.

Investors might be aware of market sentiment in their fund decisions. I employ aggregate mutual fund flow divided by aggregate fund size as a sentiment measure (Chiu and Kini, 2014; Barber, Huang and Odean, 2016). I identify a high sentiment period as the top quartile of the sentiment series and a low sentiment period as the bottom quartile. From Table 4-9 Panel A Columns 3 and 4, in a low sentiment period, fundamental characteristics and active measures show R-squareds of 60.82% and 28.29%. Their sum of R-squared (89.11%) is larger than the R-squared of CAPM alpha (5.63%). In addition, in a high sentiment period, fundamental and active measures show

[23] Due to data availability, I remove the broker-sold or direct sold analysis for the China market but use fund age to differentiate investor sophistication in this section.

R-squareds of 68.91% and 11.93% respectively. Their sum of R-squared (80.84%) is also larger than the R-squared of CAPM alpha (13.25%). It suggests that the main results in Table 4-6 are robust under different levels of market sentiment in China.

I further use fund age to investigate investor sophistication. Newly established funds may have more young and unsophisticated investors. In Table 4-9 Panel A Columns 5 and 6, in old funds, fundamental fund characteristics and active measures show R-squareds of 81.13% and 15.12% respectively. Their sum of R-squared (96.35%) is larger than the R-squared of CAPM alpha (2.26%). Also, in young funds, fundamental fund characteristics and active measures show R-squareds of 70.83% and 10.71% respectively. Their sum of R-squared (81.54%) is also larger than the R-squared of CAPM alpha (15.47%). It suggests that the main results in Table 4-6 are robust under different levels of fund age in China. Moreover, CAPM alpha has a positive coefficient of 3.182 (t=2.924) in young funds which is significant at the 1% level. While it has an insignificant coefficient of 1.420 (t=1.755) at the 5% level in old funds. The results indicate that short-term performance-chasing (Bollen and Busse, 2005) may exist in young funds, while in old funds non-risk factors may drive investors' attention more. This is also consistent with Pástor, Stambaugh and Taylor (2015) as investors in young funds are more performance-sensitive than they are in old funds.

Regarding the US market, in this section, I test my results by differentiating investor sophistication in three ways: direct-sold versus broker-sold, institutional funds versus retail funds, and a higher investor sentiment period versus a lower investor sentiment period. I hypothesize that sophisticated investors might respond more to sophisticated measures.

Broker-sold investors have been found to be relatively less sophisticated than direct-sold investors (Christoffersen, Evans and Musto, 2013). Also, Guercio and Reuter (2014) claim that fund managers have an incentive to generate alpha under direct-sold funds. But for broker-sold funds, fund managers show a weaker incentive to produce alpha. Following Barber, Huang and Odean (2016) and Sun (2014), I identify a broker-sold fund if it charges a front-end load or back-end load and it has a 12b-1 fee larger than 25 basis points. From Table 4-9 Panel B Columns 1 and 2, in broker-sold funds, fundamental fund characteristics show an R-square of 88.74% which is larger than that of CAPM alpha (10.74%). Similarly, in direct-sold funds, fundamental fund characteristics have an R-squared of 89.55% which is also larger than that of CAPM alpha (10.29%). It suggests that the main results are robust under different levels of distribution channels in the US.

Institutional investors might have sophisticated benchmarks to evaluate fund performance, while retail investors might chase past performance. From Table 4-9 Panel B Columns 3 and 4, in institutional funds, fundamental fund characteristics have an R-squared of 81.78% which is larger than that of CAPM alpha (18%). Also, in retail funds, fundamental fund characteristics have a larger explanatory power of 89.82% than that of CAPM alpha (9.71%). It confirms the robustness of the main results in Table 4-6 under different types of investor in the US. Moreover, the CAPM alpha of institutional funds shows an insignificant coefficient at 3.575 (t=1.813) at the 5% level, while the CAPM alpha of retail funds has a significant coefficient of 1.427 (t=4.442) at the 1% level. It implies that institutional investors might implement more sophisticated measures to evaluate fund performance (Barber, Huang and Odean, 2016), while retail investors appear to be performance-chasing.

Market sentiment may affect the behaviour of unsophisticated investors. To shed new light on the perspective of sentiment effect, I employ the aggregate mutual fund flows as a sentiment measure following Chiu and Kini (2014) and Baber, Huang and Odean (2016) and identify a high (low) sentiment period as the top (bottom) quartile of the overall sample period. From Table 4-9 Panel B Columns 5 and 6, in a low sentiment period, fundamental fund characteristics have an R-squared of 89.32% which is larger than that of CAPM alpha (6.53%). Also, in a high sentiment period, fundamental fund characteristics show an R-squared of 87.65% which is larger than that of CAPM alpha (8.03%). It supports the results in Table 4-6 as non-risk factors outperform risk-adjusted performance in both low and high sentiment periods in the US.

4.6.2 Scale-Decreasing Returns and Flow Determinants

Table 4-10 Scale-Decreasing Returns and Flow Determinants

This table shows predictions of quarterly fund flows with fundamental fund characteristics, CAPM alpha, market beta and their interaction term with a dummy variable that proxies for investor sophistication following Barber, Huang and Odean (2016). The dummy variable considers the impact of sale-decreasing returns from fund size, organizational diseconomies that the fund is solo-managed or co-managed, whether fund managers hold fund shares. Independent variables include risk-adjusted alpha, risk beta, active investment factor and fundamental fund characteristics. Risk-adjusted alphas and risk betas are calculated from the CAPM with 24-month/60-month rolling window regressions. Fundamental fund characteristics include log of fund size, log of fund family size, fund age, total expense ratio, log of manager tenure, lagged fund flow, annual turnover, prior 12-month return volatility and Morningstar 3-years rating. Active investment factors include fund diversification, industry concentration index (ICI), reliance on public information (RPI), fund-report attention, active share and return gap. I run double-clustered regressions to get the coefficients. Decomposed R-squareds (individual R^2 %) calculated using Shapley-own methods are listed for each regression. Regarding the regression, cluster effects are studied with standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: China

	(1) Large funds		(2) Small funds		(3) Solo-managed funds		(4) Co-managed funds		(5) Held by managers		(6) Not held by managers	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
CAPM alpha	0.936	**1.76**	3.725***	**14.83**	2.595***	**7.69**	2.378**	**17.09**	2.714***	**10.13**	1.728	**3.29**
	(1.145)		(4.131)		(3.300)		(2.252)		(3.251)		(1.639)	
CAPM beta	0.024	**9.67**	-0.021	**7.75**	0.004	**0.85**	-0.017	**0.38**	0.020	**2.72**	-0.107	**5.82**
	(0.469)		(-0.332)		(0.070)		(-0.462)		(0.364)		(-1.579)	
Fund size	-0.015	9.87	-0.034***	10.08	-0.034***	18.63	-0.020***	11.40	-0.038***	19.81	-0.008	5.39
	(-1.472)		(-5.027)		(-4.378)		(-2.951)		(-4.087)		(-0.996)	
Family size	-0.001	9.14	0.023***	6.62	0.017***	7.23	0.012*	6.08	0.023***	9.84	-0.005	6.52
	(-0.260)		(2.971)		(2.720)		(1.647)		(3.325)		(-0.795)	
Age	-0.001	7.37	0.014	1.73	0.017	1.34	-0.019	17.99	0.014	1.26	-0.006	7.01
	(-0.067)		(0.999)		(1.323)		(-1.490)		(1.510)		(-0.316)	
Expense	-0.283*	4.24	0.229	1.66	0.084	0.42	-0.116	0.62	0.114	0.96	-0.266	2.05
	(-1.681)		(0.523)		(0.257)		(-0.480)		(0.415)		(-0.923)	
Flow	0.120**	26.22	0.162***	35.13	0.167***	44.87	0.069	18.25	0.146***	40.85	0.095	12.95
	(2.066)		(2.863)		(3.248)		(1.576)		(4.233)		(1.256)	

Table 4-10 (continued)

Volatility	0.773**	10.46	0.992***	9.12	0.929***	9.61	0.891***	18.28	0.719***	6.21	1.802***	34.89
	(1.961)		(4.300)		(3.757)		(2.704)		(2.876)		(3.784)	
Fundamental subtotal R^2		**67.30**		**64.36**		**82.09**		**72.63**		**78.93**		**68.81**
Diversification	0.022**	6.91	0.022	3.05	0.026***	2.05	0.021**	3.07	0.031***	3.53	0.008	6.00
	(2.276)		(1.639)		(2.963)		(2.165)		(3.769)		(0.589)	
ICI	-0.083	1.60	0.283	4.71	0.123	1.24	-0.192	0.97	0.063	0.72	0.532*	2.86
	(-0.964)		(1.448)		(1.369)		(-0.798)		(0.720)		(1.750)	
RPI	0.005	0.58	0.021	1.22	0.031*	1.68	-0.020	1.07	0.007	0.67	0.058*	2.61
	(0.222)		(0.870)		(1.660)		(-0.741)		(0.299)		(1.935)	
Fund attention	0.046	9.77	0.018	2.23	0.041*	3.39	0.028	3.67	0.030	2.40	0.055*	8.33
	(1.341)		(1.016)		(1.955)		(0.942)		(1.368)		(1.814)	
Active Share	-0.010	1.37	-0.112*	1.29	-0.048	0.33	-0.014	0.15	-0.025	0.19	-0.086	1.71
	(-0.318)		(-1.707)		(-1.120)		(-0.177)		(-0.565)		(-1.240)	
Return Gap	0.029	1.04	0.035	0.58	0.038	0.69	-0.019	0.97	0.042	0.72	-0.006	0.58
	(0.814)		(0.787)		(0.971)		(-0.407)		(1.081)		(-0.115)	
Active subtotal R^2		**21.28**		**13.07**		**9.37**		**9.90**		**8.22**		**22.09**
Intercept	-0.016*		-0.066***		-0.042***		-0.042***		-0.065***		-0.036***	
	(-1.790)		(-4.287)		(-3.337)		(-4.587)		(-3.137)		(-4.665)	
Cluster quarter effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	4,688		4,688		4,688		4,688		4,688		4,688	
R-squared	0.0264		0.0497		0.0522		0.0103		0.0514		0.0166	
Adj. R-squared	0.0235		0.0469		0.0493		0.00733		0.0486		0.0136	

Table 4- 10 (continued)

Panel B: The US

	(1) Large funds		(2) Small funds		(3) Solo-managed funds		(4) Co-managed funds		(5) Held by managers		(6) Not held by managers	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
CAPM alpha	1.228***	**8.09**	2.684***	**11.47**	1.368***	**9.45**	1.810***	**11.01**	1.822***	**11.46**	1.161***	**5.89**
	(5.135)		(3.733)		(4.061)		(4.464)		(4.407)		(3.007)	
CAPM beta mkt	-0.004	**10.54**	-0.017	**5.68**	0.002	**0.58**	-0.015	**0.21**	-0.003	**0.03**	-0.030	**1.04**
	(-0.747)		(-0.739)		(0.213)		(-1.168)		(-0.319)		(-0.903)	
Fund size	-0.005***	4.52	-0.015***	6.76	-0.012***	7.02	-0.015***	8.26	-0.013***	5.64	-0.015***	12.38
	(-7.241)		(-5.811)		(-5.880)		(-4.587)		(-7.661)		(-2.639)	
Family size	0.002***	3.53	0.013***	10.86	0.007***	4.62	0.012***	7.36	0.008***	3.98	0.014*	14.32
	(3.945)		(4.466)		(6.043)		(3.199)		(7.169)		(1.959)	
Age	-0.008***	6.62	-0.023*	7.03	-0.007**	4.93	-0.013**	6.65	-0.007***	3.93	-0.023**	13.76
	(-8.303)		(-1.813)		(-1.964)		(-2.552)		(-3.493)		(-2.012)	
Expense	0.001	1.19	0.010	1.42	0.004**	0.48	0.006	0.72	0.004*	0.58	0.006	1.11
	(1.483)		(1.480)		(2.081)		(1.416)		(1.931)		(0.899)	
Tenure	0.128	1.44	-0.235	0.78	1.916***	3.47	0.316	0.43	2.155***	3.52	-2.469	4.37
	(0.806)		(-0.096)		(4.188)		(0.214)		(5.973)		(-0.815)	
Flow	0.313***	48.44	0.293***	35.24	0.307***	52.41	0.304***	47.35	0.340***	52.08	0.212***	28.17
	(19.724)		(12.988)		(10.885)		(17.469)		(21.211)		(6.667)	
Turnover	-0.005***	1.06	0.013	2.12	0.005	0.70	0.004	0.49	-0.004	0.11	0.024	5.77
	(-3.088)		(1.263)		(1.513)		(0.602)		(-1.491)		(1.407)	
Volatility	-0.106	1.85	0.552	2.61	-0.185	0.65	0.251	0.64	-0.162	0.34	0.729	5.10
	(-1.518)		(0.766)		(-1.596)		(0.691)		(-1.479)		(0.853)	
MS 3-year rating	0.016***	12.72	0.024***	16.04	0.021***	15.70	0.021***	16.88	0.023***	18.33	0.014***	8.08
	(18.167)		(5.743)		(9.761)		(10.108)		(12.859)		(4.333)	

Table 4-10 (continued)

Fundamental subtotal R^2	**81.37**	**82.86**	**89.97**	**88.78**	**88.51**	**93.07**
Intercept	0.048***	0.009***	0.025***	0.022***	0.022***	0.026***
	(6.364)	(4.969)	(6.121)	(6.430)	(2.683)	(9.043)
Cluster quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,629	123,629	123,629	123,629	123,629	123,629
R-squared	0.0032	0.0048	0.0017	0.0051	0.0056	0.0017
Adj. R-squared	0.00311	0.00473	0.00165	0.00502	0.00552	0.00165

In terms of the China market, in this section, I test whether my results are affected by funds exposed to different degrees of scale-decreasing returns. I hypothesize that investors might recognize potential factors including fund size, organizational diseconomies and manager ownerships, which might cause scale-decreasing returns (Chen et al., 2004). I measure organizational diseconomies with a dummy to differentiate between solo-managed and co-managed funds.

The size effect that funds tend to underperform as their size grows has been well-documented in the literature. Chen et al. (2004) find that scale–decreasing returns are attributable to fund liquidity and organizational diseconomies. Funds with small-cap holdings suffer from a liquidity problem, and co-managed funds suffer from the hierarchy cost which explains scale-decreasing returns. Also, Khorana, Servaes and Wedge (2007) find that portfolio ownership of fund managers is positively associated with fund performance. I assume that funds with a large size, co-managed funds and funds not held by fund managers have higher exposure to scale-decreasing returns. From Table 4-10 Panel A Columns 1 and 2, in small funds, fundamental fund characteristics and active measures have R-squareds of 64.36% and 13.07% respectively. Their sum of R-squared (77.43%) is larger than that of CAPM alpha (14.83%). In large funds, fundamental fund characteristics and active measure have R-squareds of 67.3% and 21.28%. Their sum of R-squared (88.58%) is also larger than that of CAPM alpha (1.76%). It indicates that the main results in Table 4-6 are robust under different levels of funds size in China. Moreover, CAPM alpha in small funds has a positive and significant coefficient of 3.725 (t=4.131) at the 1% level, while in large funds it has an insignificant coefficient of 0.936 (t=1.145) at the 10% level. It suggests that investors in small funds are sensitive to CAPM alpha, while they respond less to CAPM alpha in large funds.

From Column 3 and 4, in solo-managed funds, fundamental fund characteristics and active measure show R-squareds of 82.09% and 9.37%. Their sum of R-squared (91.46%) is larger than the R-squared of CAPM alpha (7.69%). In co-managed funds, fundamental fund characteristics and active measure have R-squareds of 72.63% and 9.9% respectively. Their sum of R-squared (82.53%) is also larger than the R-squared of CAPM alpha (17.09%). It confirms the main results in Table 4-6 are robust under different management structures in China.

From Columns 5 and 6, in the funds held by managers, fundamental fund characteristics and active measures have R-squareds of 78.93% and 8.22%. Their sum of R-squared (87.15%) is larger than the R-squared of CAPM alpha (10.13%). In the funds that are not held by managers, fundamental fund characteristics and active measures have R-squareds of 68.81% and 22.09%. Their sum of R-squared (90.9%) is also larger than that the R-squared of CAPM alpha (3.29%). It confirms the main results in Table 4-6 under different types of managerial ownership in China. Moreover, in funds held by managers, CAPM alpha has a positive and significant coefficient of 2.714 (t=3.251) at the 1% level, while it has an insignificant coefficient of 3.29 (t=1.639) at the 10% level in funds without managers' ownership. This might be attributable to an agency conflict in funds without manager ownership. Fund managers might have an incentive to maximize the profit of the company rather than the risk-adjusted returns of investors (Chevalier and Ellison, 1997).

For the US market, I also assume that funds with larger size, co-managed funds and funds not held by fund managers, have higher exposure to scale-decreasing returns. From Table 4-10 Panel B Columns 1 and 2, in large funds, fundamental fund characteristics have an R-squared of 81.37% which is larger than that of CAPM alpha (8.09%). In small funds, it has an R-squared of 82.86% which is also larger than that of CAPM alpha (11.47%). It confirms that the main results in Table 4-6 are robust under different levels of fund size in the US. From Columns 3 and 4, in solo-managed funds, fundamental fund characteristics have an R-squared of 89.97% which is larger than that of CAPM alpha (9.45%). In co-managed funds, it has an R-squared of 88.78% which is also larger than that of CAPM alpha (11.01%). It indicates that the main results in Table 4-6 are robust under different levels of management structure in the US. Also, Kaniel, Tompaidis and Zhou (2017) suggest that fund managers who commit their wealth affect risk-taking in their fund investments. From Columns 5 and 6, in the funds held by managers, fundamental fund characteristics have an R-squared of 88.51% which is larger than that of CAPM alpha (11.46%). While in the funds not held by managers, fundamental fund characteristics have an R-squared of 93.07% which is also larger than that of CAPM alpha (5.89%). It confirms the robustness of the main results in Table 4-6 under different levels of managerial ownership in the US.

4.6.3 Participation Costs and Flow Determinants

Investors might have a different response to fund performance when the participation costs of funds differ. Sirri and Tufano (1998) find that search costs can affect the flow-performance relationships. Huang, Wei and Yan (2007) also find that investors respond to mutual fund performance differently due to participation costs. I split the sample with different levels of participation costs in the robustness test of this section.[24]

In terms of the Chinese market, in this section, I evaluate the robustness of search costs and participation costs affecting investors' fund decisions. I address the issue that investors might react differently to a large fund family, high-expense funds and star funds. From Table 4-11 Panel A Columns 1 and 2, fundamental fund characteristics have larger R-squareds in both high fees and low fees funds than those of CAPM alpha. Moreover, investors in higher management fee funds attach more weight to active measures (11.53%) than CAPM alpha (8.55%), while investors in lower management fee show more concerns over CAPM alpha (10.09%) than that of active measures (5.39%). It indicates that the results in Table 4-6 are robust under different levels of fund fees in China. Active investment is expected to reward investors with higher premiums (Pollet and Wilson, 2008; Cremers and Petajisto, 2009). The results indicate that investors may expect to be compensated for management costs from active investment skills in high-fee funds. From Columns 3 and 4, in large fund families, fundamental fund characteristics show an R-squared of 81.46% which is larger than that of CAPM alpha (3.24%). In small fund families, the R-square of fundamental fund characteristics (74.91%) is also larger than that of CAPM alpha (12.88%). It suggests the main results in Table 4-6 are robust under different levels of family size. In addition, I define a fund with a recent Morningstar rating of 4 or 5 as a star fund. From Columns 5 and 6, fundamental fund characteristics have larger R-squared than those of CAPM

[24]Robustness test controlling for star and non-star funds is applied to the China market. As Morningstar ratings have already been included in control variables in the US regression, this section uses fund age rather than a dummy variable for star funds to check robustness in the US market.

alpha in both star and non-star funds. Moreover, the R-squared of active measures (16.49%) in star funds is larger than that of CAPM alpha (11.60%), while in non-star funds active measures show a smaller R-squared of (7.08%) than that of CAPM alpha (7.93%) This may imply that star funds are expected more by investors from the perspectives of sophisticated benchmarks and active management skill.

In terms of the US market, investors might have a different response to fund performance when the participation costs of funds differ. I address the issue that investors might react differently to large fund family, high-expense funds and young funds. Fundamental fund characteristics show larger explanatory powers than those of CAPM alpha under different levels of fund fee, fund family size and fund age. For example, in Column 1, fundamental fund characteristics have an R-squared of 89.36% which is larger than that of CAPM alpha (10.58%). The results are consistent with the main analysis in Table 4-6 as non-risk factors outperform risk factors and risk-adjusted alpha in explaining fund flows under different levels of participation costs in the US.

Table 4-11 Participation Costs and Flow Determinants

This table shows predictions of quarterly fund flows with fund fundamental characteristics, CAPM alpha, market beta and an interaction term with a dummy variable that proxies for investor sophistication following Barber, Huang and Odean (2016). The dummy variables consider participation costs for investors from high fee or low fee funds, large or small fund families, star or non-star funds, and old or young funds. The independent variables include risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics. Risk-adjusted alphas and risk betas are calculated from the CAPM with 24-month/60-month rolling window regressions. Fundamental fund characteristics include log of fund size, log of fund family size, fund age, total expense ratio, log of manager tenure, lagged fund flow, annual turnover, prior 12-month return volatility and Morningstar 3-year rating. Active investment factors include fund diversification, industry concentration index (ICI), reliance on public information (RPI), fund-report attention, active share and return gap. I run double-clustered regressions to get coefficients. Decomposed R-squareds (individual R^2 %) calculated using Shapley-own methods are listed for each regression. Regarding the regression, cluster effects are studied with standard errors clustered at both the fund level and the quarter level. ***, ** and * denote the significance at 1%, 5% and 10% levels respectively.

Panel A: China

	(1) High fees		(2) Low fees		(3) Large fund family		(4) Small fund family		(5) Star funds		(6) Non-star funds	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
CAPM alpha	2.774***	**8.55**	2.151**	**10.09**	0.961	**3.24**	3.591***	**12.88**	2.974***	**11.60**	2.299***	**7.93**
	(3.619)		(2.293)		(1.188)		(4.275)		(2.926)		(2.672)	
CAPM beta	0.036	**0.88**	-0.055	**1.62**	-0.041	**3.88**	0.019	**2.63**	-0.016	**0.47**	-0.004	**0.71**
	(0.533)		(-1.034)		(-0.669)		(0.269)		(-0.286)		(-0.081)	
Fund size	-0.032***	16.65	-0.030***	18.61	-0.024**	14.37	-0.035***	16.56	-0.033***	19.99	-0.031***	15.66
	(-4.315)		(-4.353)		(-2.225)		(-6.322)		(-4.305)		(-4.177)	
Family size	0.011***	5.94	0.020***	10.62	0.015*	7.74	0.016***	6.24	0.017**	8.88	0.016***	6.25
	(2.938)		(2.617)		(1.880)		(2.738)		(2.325)		(3.001)	
Age	0.010	1.67	0.006	3.81	-0.006	9.91	0.013	1.17	-0.002	4.81	0.016	1.73
	(0.860)		(0.336)		(-0.478)		(0.950)		(-0.137)		(1.570)	
Expense	0.485	1.45	0.041	0.98	-0.318	1.60	0.207	0.71	-0.367	0.54	0.200	0.56
	(0.538)		(0.127)		(-1.178)		(0.518)		(-0.843)		(1.260)	
Flow	0.177***	45.91	0.104***	30.24	0.103**	36.24	0.186***	40.08	0.111***	26.54	0.171***	48.55
	(2.859)		(3.292)		(2.574)		(2.984)		(4.196)		(3.257)	

Table 4-11 (continued)

Volatility	0.818***	7.43	1.041***	18.63	0.765**	11.61	1.041***	10.15	0.887***	10.68	0.985***	11.52
	(3.989)		(3.058)		(2.183)		(4.195)		(3.571)		(3.196)	
Fundamental subtotal R^2		**79.04**		**82.90**		**81.46**		**74.91**		**71.44**		**84.27**
Diversification	0.028***	2.25	0.021*	2.59	0.020	4.31	0.030***	1.92	0.028	2.35	0.022***	2.06
	(4.192)		(1.667)		(1.520)		(3.382)		(1.573)		(2.657)	
ICI	0.181	0.93	0.019	0.72	-0.048	0.37	0.399**	3.28	0.209	1.03	0.051	0.74
	(1.400)		(0.156)		(-0.404)		(2.037)		(0.569)		(0.733)	
RPI	0.041*	1.65	-0.006	0.35	0.015	0.54	0.011	0.75	0.067**	6.86	-0.014	0.35
	(1.655)		(-0.333)		(0.772)		(0.418)		(2.576)		(-0.471)	
Fund attention	0.052***	5.33	0.016	1.41	0.026	4.30	0.041**	2.63	0.049**	4.35	0.032	3.24
	(2.734)		(0.510)		(0.856)		(2.203)		(2.025)		(1.414)	
Active Share	-0.072*	0.44	0.015	0.21	0.017	0.84	-0.085	0.61	-0.109	1.49	0.012	0.24
	(-1.666)		(0.235)		(0.322)		(-1.483)		(-1.276)		(0.317)	
Return Gap	0.052	0.93	0.007	0.12	0.035	1.05	0.028	0.40	0.041	0.41	0.030	0.45
	(1.002)		(0.227)		(1.259)		(0.680)		(1.107)		(0.785)	
Active subtotal R^2		**11.53**		**5.39**		**11.42**		**9.58**		**16.49**		**7.08**
Intercept	-0.043***		-0.042***		-0.032***		-0.054***		-0.044***		-0.040***	
	(-3.967)		(-4.241)		(-3.452)		(-4.517)		(-3.957)		(-4.319)	
Cluster quarter effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	4,688		4,688		4,688		4,688		4,688		4,688	
R-squared	0.0421		0.0201		0.0168		0.0500		0.0213		0.0405	
Adj. R-squared	0.0393		0.0171		0.0138		0.0471		0.0184		0.0377	

Table 4-11 (continued)

Panel B: The US

	(1) High fees		(2) Low fees		(3) Large fund family		(4) Small fund family		(5) Old funds		(6) Young funds	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
CAPM alpha	1.730***	**10.58**	1.669***	**9.68**	1.026***	**7.00**	2.910***	**13.30**	1.740***	**10.24**	1.858***	**8.57**
	(3.649)		(4.306)		(3.616)		(4.363)		(4.876)		(3.514)	
CAPM beta mkt	0.004	**0.06**	-0.017	**0.92**	-0.005	**0.98**	-0.026	**0.72**	-0.000	**13.09**	-0.030	**8.21**
	(0.390)		(-0.952)		(-0.749)		(-1.059)		(-0.046)		(-1.266)	
Fund size	-0.015***	6.51	-0.012***	7.72	-0.012***	6.97	-0.029**	13.47	-0.011***	10.14	-0.020***	7.86
	(-7.324)		(-3.416)		(-10.170)		(-2.487)		(-6.161)		(-4.016)	
Family size	0.010***	5.55	0.010**	6.46	0.008***	4.95	0.026**	14.65	0.005***	5.86	0.015***	9.90
	(6.930)		(2.068)		(7.662)		(2.047)		(4.873)		(2.984)	
Age	-0.011***	4.66	-0.012*	7.80	-0.009***	5.70	-0.017*	6.70	-0.002	5.98	-0.006	2.81
	(-4.586)		(-1.904)		(-5.215)		(-1.853)		(-0.791)		(-0.602)	
Expense	0.003	0.44	0.011	1.86	0.003**	0.47	0.011	0.95	0.004***	1.68	0.007	1.50
	(1.289)		(1.531)		(2.184)		(1.356)		(3.074)		(0.822)	
Tenure	2.526***	3.94	-4.122	3.54	1.691***	2.95	-1.075	0.47	1.018**	1.80	-0.450	1.24
	(5.323)		(-0.853)		(4.057)		(-0.448)		(2.374)		(-0.182)	
Flow	0.296***	47.48	0.315***	45.60	0.323***	54.93	0.286***	33.72	0.280***	36.02	0.321***	40.53
	(16.726)		(12.572)		(18.995)		(12.109)		(14.646)		(15.705)	
Turnover	-0.001	0.18	0.013	1.63	-0.003	0.18	0.010	1.24	-0.002	0.75	0.014	2.45
	(-0.303)		(1.028)		(-1.611)		(1.010)		(-0.666)		(1.093)	
Volatility	-0.263**	0.57	0.540	2.40	-0.198**	0.87	0.542	2.03	-0.093	1.83	0.566	2.41
	(-2.334)		(0.942)		(-2.018)		(0.858)		(-1.111)		(0.731)	
MS 3-year rating	0.025***	20.02	0.017***	12.39	0.020***	15.00	0.019***	12.75	0.018***	12.62	0.024***	14.52
	(12.692)		(7.913)		(13.539)		(5.401)		(11.482)		(8.096)	

Table 4-11 (continued)

Fundamental subtotal R^2	**89.36**	**89.40**	**92.02**	**85.98**	**76.67**	**83.22**
Intercept	0.021***	0.029***	0.029***	0.020***	0.056***	0.007***
	(3.945)	(8.741)	(4.518)	(8.251)	(7.188)	(2.915)
Cluster quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,629	123,629	123,629	123,629	123,629	123,629
R-squared	0.0041	0.0029	0.0035	0.0042	0.0034	0.0047
Adjusted R-squared	0.00404	0.00286	0.00337	0.00414	0.00333	0.00458

In sum, the results of the robustness test are consistent with Hypothesis Two. They further confirm that non-risk factors show better explanatory power for fund flows than risk factors and risk-adjusted performance. In addition, the robustness tests also show some evidence that sophisticated investors utilize advanced benchmarks in fund selection (Barber, Huang and Odean, 2016).

4.7 Practical Performance Implications: Smart-to-Dumb Ratio (SDR)

I further investigate the practical application of decomposed R-squared in performance predictions. As the US sample contains relatively adequate observations and horizons for decomposing R-squared at the individual fund level, I proceed to examine the application of decomposed R-squared in the US market. First, I examine how US investors react to a wide range of flow determinants. Second, I propose a new predictor for identifying well-performing US funds, Smart-to-Dumb Ratio (SDR). Third, I examine its performance implications. Finally, to further check the robustness of SDR in identifying superior funds, I study the impact of SDR on fund family strategies, primer broker comovement, Morningstar ratings and anomaly returns.

4.7.1 Which Factors Drive Fund Flows on the Individual Fund Level in the US?

To further assess which flow determinants investors tend to use in their fund decisions on the individual fund-level in the US, I regress fund flow on a wide range of fund flow determinants to set up a regression specification for decomposing R-squared. Specifically, I regress fund flow on fundamental fund characteristics and alphas computed from six asset pricing models, including the CAPM, the Fama-French model, the Fama-French-Carhart model, the Fama-French five-factor model, the Q-factor model from Hou, Xue and Zhang (2014) and the mispricing-factor model from Stambaugh and Yuan (2016). Following Agarwal, Green and Ren (2018), I define the CAPM and the Fama-French three-factor model as traditional risk models and define the others as exotic risk models. Fund characteristics and Morningstar ratings are also included in the regression.

Table 4-12 Which Factors Drive Fund Flows in the US?

This table reports the results of the regression comparing the impact of different risk-adjusted performance on fund flows. The first column includes fund return, market excess return and CAPM alpha. The traditional risk column includes risk-adjusted performance from the CAPM and the Fama-French three-factor model (FF3); the exotic risk column includes risk-adjusted performance from the Fama-French Carhart model (FF4), the Fama-French five-factor model (FF5), the Q-factor model (QF) from Hou, Xue and Zhang (2014) and the mispricing-factor model (MF) from Stambaugh and Yuan (2016). The dependent variable is monthly fund flow at month *t*+1. Independent variables include risk-adjusted alpha and risk beta calculated with 60-month rolling window regressions. They also include Morningstar overall ratings and fundamental fund characteristics including log of fund size, log of fund family size, fund turnover, fund age, total expense ratio, prior 12-month return volatility and flow volatility and lagged flow. I run double-clustered regressions to obtain the coefficients. Decomposed R-squareds (individual R^2 %) calculated using Shapley-own methods are listed for each regression. Standard errors are clustered at both the fund level and the month level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Dependent variable: Fund flows in month *t*+1

	(1) Traditional risk		(2) Traditional risk		(3) Exotic risk		(4) All risk	
Variables	**Coeff.**	**Ind R^2**	**Coeff.**	**Ind R^2**	**Coeff.**	**Ind R^2**	**Coeff.**	**Ind R^2**
Fund return	0.020**	1.22	0.021**	1.32	0.013*	1.06	0.017**	1.24
	(2.368)		(2.483)		(1.770)		(2.102)	
Market excess return	0.104***	3.21	0.103***	3.06	0.109***	3.12	0.108***	3.05
	(5.994)		(6.044)		(6.839)		(6.574)	
CAPM alpha	1.264***	33.41	0.835***	19.29			0.578***	12.05
	(16.795)		(9.060)				(6.253)	
FF3 alpha			0.756***	18.33			0.061	10.62
			(6.837)				(0.283)	
Traditional risk subtotal R^2		**37.84**		**42.00**		**4.18**		**26.96**
FF4 alpha					0.500***	11.12	0.427***	6.93
					(3.404)		(2.631)	
FF5 alpha					0.339***	9.33	0.141	5.42
					(2.774)		(0.795)	

Table 4-12 (continued)

QF alpha					0.371***	6.92	0.279***	4.24
					(4.812)		(3.653)	
MF alpha					0.561***	10.26	0.313**	6.25
					(4.058)		(2.376)	
Exotic risk subtotal R^2						**37.62**		**22.84**
MS overall rating	0.008***	**38.51**	0.007***	**35.72**	0.008***	**36.06**	0.007***	**29.70**
	(19.494)		(18.717)		(19.254)		(18.210)	
Fund size (log)	-0.003***	2.95	-0.003***	2.76	-0.003***	2.90	-0.003***	2.76
	(-9.513)		(-9.126)		(-9.200)		(-9.215)	
Family size (log)	0.001***	0.92	0.001***	0.83	0.001***	0.82	0.001***	0.77
	(5.949)		(5.600)		(5.479)		(5.583)	
Age (month)	0.000**	0.22	0.000**	0.22	0.000*	0.25	0.000*	0.22
	(2.401)		(2.172)		(1.680)		(1.782)	
Expense ratio	0.109	0.45	0.118	0.43	0.204*	0.54	0.166	0.43
	(1.031)		(1.122)		(1.871)		(1.516)	
Flow	0.055***	15.67	0.054***	15.04	0.054***	14.95	0.054***	13.79
	(4.445)		(4.413)		(4.396)		(4.375)	
Category flow	0.000**	0.80	0.000***	0.82	0.000***	0.85	0.000**	0.63
	(2.190)		(2.588)		(3.096)		(2.382)	
Turnover	-0.001	0.37	-0.001	0.30	-0.000	0.27	-0.000	0.24
	(-1.643)		(-1.288)		(-0.247)		(-0.779)	
Flow volatility	0.027***	1.51	0.027***	1.46	0.026***	1.45	0.026***	1.34
	(3.511)		(3.508)		(3.385)		(3.395)	
Return volatility	-0.068***	0.77	-0.051***	0.42	-0.010	0.10	-0.036*	0.30
	(-3.426)		(-2.629)		(-0.527)		(-1.808)	
Characteristics subtotal R^2		**23.65**		**22.28**		**22.14**		**20.49**
Non-risk factors subtotal R^2		**62.16**		**58.00**		**58.20**		**50.19**

Table 4-12 (continued)

Intercept	0.003	0.003	-0.000	0.002
	(0.518)	(0.528)	(-0.024)	(0.461)
Cluster month effects	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes
Observations	171,580	171,580	171,580	171,580
R-squared	0.0236	0.0242	0.0243	0.0247
Adjusted R-squared	0.0235	0.0241	0.0242	0.0246

First, I find that the CAPM alpha significantly drives fund flows. In Table 4-12 Column 4, CAPM alpha has a positive and significant coefficient at the 1% level (0.578, t=6.253) and a large R-squared of 12.05%. It indicates that 1% of CAPM alpha leads to an average increase of 0.578% of fund flows. Consistent with Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016), CAPM alpha dominates in directing fund flows. Second, the alphas from the Q-factor model and mispricing-factor model significantly explain fund flows with coefficients of 0.279 (t=3.653) and 0.313 (t=2.376) respectively. Third, the Morningstar rating group shows the largest explanatory power to drive fund flows. It ranges from 29.70% to 38.51%. This is consistent with Guercio and Tkac (2008) and Nanda, Wang and Zheng (2004) as Morningstar ratings have considerable power to drive fund flows in the US market. Also, fund flow has its highest R-squared among the fund characteristic group ranging from 13.79% to 15.67%. It suggests that investors are aware of the smart money effect in their fund decisions. (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). In the next section, I further take the regression specification (4) in the rolling window regressions to compute decomposed R-squared of each flow determinant.

4.7.2 SDR and Fund Performance

On the one hand, the literature shows that if investors purchase funds based on past superior performance, they cannot obtain persistent outperformance since Brown and Goetzmann (1995) find that fund performance persistence varies with the period. Bollen and Busse (2005) also find that the fund performance persistence found by Carhart (1997) disappears if sorting funds by past returns, while they show performance persistence only exists in the short-term, a three-month period, on sorting funds by four-factor alphas. For performance as the determinant of fund flows, the CAPM has been found to be the dominant risk model used by investors for directing their fund flows (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016). This is puzzling given the inability of CAPM to predict cross-sectional stock returns. The explanation of this puzzle is still under debate. Barber, Huang and Odean (2016) suggest that investors make behavioural mistakes by using simpler risk models. This is in line with other literature showing that performance is not persistent (Brown and Goetzmann, 1995). It suggests that performance tracing can contribute to the mistakes made by naive investors (Karceski, 2002).

On the other hand, non-risk factors have been documented to be important fund flow determinants. Barber, Huang and Odean (2016) argue that smart investors should consider all factors, whether priced or unpriced, to identify superior funds. Studies show that the fund size significantly erodes fund performance (Chen et al., 2004; Harvey and Liu, 2017). In addition, funds receiving higher past flow tend to outperform their peers subsequently (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). Thus, I expect that sophisticated investors will employ unpriced non-risk factors in their fund decisions. Fundamental fund characteristics such as fund size, lagged flows and expense ratio have been found to significantly affect mutual fund performance (Chen et al., 2004, Pollet and Wilson, 2008; Keswani and Stolin, 2008; Zheng, 1999; Huang, Wei and Yan, 2007). Furthermore, the persistence of mutual fund performance has been found to be short-lived and to vary over time periods (Hendricks, Patel and Zeckhauser, 1993; Carhart, 1997; Bollen and Busse, 2005). This suggests that investors who determine their fund allocation on fundamental fund characteristics are smarter than those who determine on past performance.

Given this argument, I hypothesize that funds that experience higher proportions of fund flows driven by funds' fundamental fund characteristics rather than by funds' past performance tend to achieve better performance. In other words, I see fund flows explained by fundamental fund characteristics as 'smart' flows while fund flows explained by past performance are 'dumb' money. The relative Smart-to-Dumb Ratio will predict future fund performance. Empirically, I run flow determinant regressions using net flow as the dependent variable following existing literature (Sirri and Tufano, 1998; Huang, Wei and Yan, 2007; Coval and Stafford, 2007; Barber, Huang and Odean, 2016; Franzoni and Schmalz, 2017). Independent variables are constructed at the beginning of the fund flow measurement period following Coval and Stafford (2007) and Barber, Huang and Odean (2016).

Following Column 4 in Table 4-12, I regress the fund flow at month *t* on traditional risk-adjusted performance, exotic risk-adjusted performance, Morningstar rating and fund characteristics at month *t*-1 using 60-month rolling windows. I obtain the decomposed R-squared of these four groups of regressors for each fund at month *t*.

$$Flow_{i,t} = \beta_0 + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + \sum \beta_i^{rating} * MS\ ratings_{i,t} + \sum \beta_i^{traditional} * traditional\ \ performance_{i,t-1} + \sum \beta_i^{exotic} * exotic\ performance_{i,t} + \varepsilon_{i,t}$$

(Eq. 4-9)

Then, I define the Smart-to-Dumb Ratio (SDR) as fundamental characteristics R-squared divided by exotic performance R-squared.

$$SDR = \frac{decomposed\ R^2\ from\ fundamental\ fund\ characteristics}{decomposed\ R^2\ from\ risk-adjusted\ performance}$$

(Eq. 4-10)

Where the numerator is the decomposed R-squared of fundamental fund characteristics, it measures to what extent investors purchase funds based on fundamental fund characteristics. The denominator is the decomposed R-squared of risk-adjusted performance based on exotic risk measures using the Fama-French-Carhart model, the Fama-French five-factor model, the Q-factor model from Hou, Xue and Zhang (2014) and the mispricing-factor model from Stambaugh and Yuan (2016).[25]

4.7.2.1 Long-Short Portfolios Sorted by SDR

To examine the predictive power of SDR for fund performance, I construct long-short fund portfolios based on SDR. For each month from 2004 to 2016, I sort funds into ten portfolios based on their SDRs. Then, I track the performance of these portfolios in the following three months to two years period. Equal-weighted and value-weighted portfolio returns are computed for each portfolio; next, I calculate risk-adjusted returns with the Fama-French-Carhart model by regressing excess returns on market risk, size risk, value risk, and momentum risk factors. The *t*-statistics of estimates are calculated using the Newey-West method with twelve lags. [26]

[25] As Agarwal, Ren and Green (2018) suggest that the skills of hedge fund managers are mainly from their exotic beta, I use exotic performance R-squared as a denominator in the construction of SDR. Main results are similar if I use the sum of traditional performance R-squared and exotic performance R-squared as a denominator.

[26] Following the practice of Greene (2002), optimal lag is determined as the smallest integer that is equal to the 1/4 power of the number of observations. Referring to Greene's approach, I utilize monthly data for risk-adjusted regressions and take twelve lags in the Newey-West corrections. The main results are not sensitive to the length of lags.

Table 4-13 SDR and Fund Performance

This table reports abnormal returns and risk exposures to returns of the long-short fund portfolios. For each month from 2004 to 2016, I sort funds into ten portfolios based on their SDR, defined as characteristics R-squared divided by performance R-squared based on fund flows. Following Jegadeesh and Titman (1993), the portfolio is rebalanced every month and held for three months to two years. Equal-weighted and value-weighted average returns across portfolios in each month are adjusted with the Fama-French-Carhart model, by regressing the excess return of the monthly portfolio on the return of risk factors. Top is the tenth decile portfolio with the highest SDR, bottom is the first decile portfolio with the lowest SDR, and Top-Bottom is a spread portfolio that buys the tenth decile portfolio and shorts the first decile portfolio. Panel A takes net fund returns and Panel B takes gross returns to calculate abnormal returns. Abnormal returns and their risk exposures are reported with *t*-statistics, computed as standard errors corrected in Newey-West methods with twelve lags. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: Net returns

SDR deciles	Alpha	MKT	SMB	HML	UMD	Alpha	MKT	SMB	HML	UMD
3-month										
	Equal-weighted					Value-weighted				
Top	-0.0286%	1.015	0.250	-0.047	0.003	0.0030%	1.018	0.155	-0.051	-0.005
	(-0.81)	(70.91)	(11.3)	(-1.67)	(0.14)	(0.07)	(87.55)	(7.02)	(-2.72)	(-0.26)
Bottom	-0.0935%	1.033	0.248	-0.068	0.002	-0.0924%	1.038	0.111	-0.120	-0.011
	(-2.29)	(59.09)	(13.04)	(-2.37)	(0.12)	(-1.81)	(46.87)	(4.62)	(-3.58)	(-0.48)
Top-Bottom	0.0649%	-0.018	0.002	0.021	0.001	0.0954%	-0.019	0.044	0.069	0.005
	(3.98)***	(-3.18)***	(0.12)	(3.03)***	(0.16)	(2.08)**	(-1.12)	(1.73)*	(2.67)***	(0.76)
6-month										
	Equal-weighted					Value-weighted				
Top	-0.0221%	1.015	0.247	-0.054	0.001	0.0064%	1.019	0.152	-0.055	-0.011
	(-0.62)	(76.41)	(12.04)	(-2.06)	(0.03)	(0.17)	(84.27)	(7.73)	(-2.86)	(-0.52)
Bottom	-0.0931%	1.031	0.244	-0.076	-0.005	-0.0951%	1.036	0.111	-0.121	-0.018
	(-2.21)	(57.98)	(13.41)	(-2.67)	(-0.32)	(-1.87)	(45.78)	(4.93)	(-3.6)	(-0.91)
Top-Bottom	0.0709%	-0.017	0.003	0.023	0.006	0.1015%	-0.017	0.042	0.066	0.008
	(3.94)***	(-2.55)**	(0.18)	(3.14)***	(1.32)	(2.33)**	(-0.96)	(1.8)*	(2.69)***	(1.1)

Table 4-13 (continued)

12-month

	Equal-weighted					Value-weighted				
Top	-0.0271%	1.016	0.242	-0.055	0.000	-0.0068%	1.022	0.151	-0.054	-0.008
	(-0.74)	(72.97)	(12.37)	(-2.03)	(-0.02)	(-0.18)	(74.76)	(8.37)	(-2.4)	(-0.37)
Bottom	-0.0921%	1.032	0.233	-0.076	-0.009	-0.0964%	1.034	0.103	-0.107	-0.024
	(-2.05)	(57.25)	(13.64)	(-2.78)	(-0.62)	(-1.86)	(47.23)	(5.51)	(-3.31)	(-1.46)
Top-Bottom	0.0650%	-0.016	0.009	0.021	0.008	0.0896%	-0.011	0.048	0.053	0.016
	(3.23)***	(-2.55)**	(0.62)	(3.01)***	(1.9)*	(2.19)**	(-0.69)	(2.92)***	(2.76)***	(1.91)*

24-month

	Equal-weighted					Value-weighted				
Top	-0.0660%	1.021	0.245	-0.072	-0.004	-0.0549%	1.029	0.151	-0.082	-0.012
	(-1.83)	(68.15)	(12.31)	(-2.93)	(-0.29)	(-1.52)	(62.35)	(7.88)	(-2.8)	(-0.55)
Bottom	-0.1124%	1.036	0.231	-0.088	-0.011	-0.1206%	1.038	0.101	-0.108	-0.026
	(-2.58)	(61.72)	(13.56)	(-3.41)	(-0.73)	(-2.63)	(54.44)	(5.99)	(-3.66)	(-1.41)
Top-Bottom	0.0464%	-0.015	0.014	0.016	0.007	0.0656%	-0.009	0.051	0.026	0.015
	(2.89)***	(-4.44)***	(1.22)	(3.21)***	(2.33)**	(2.9)***	(-1.09)	(4.65)***	(3.01)***	(2.9)***

Table 4-13 (continued)
Panel B: Gross returns

SDR deciles	Alpha	MKT	SMB	HML	UMD	Alpha	MKT	SMB	HML	UMD
3-month										
	Equal-weighted					Value-weighted				
Top	0.065%	1.016	0.250	-0.047	0.003	0.083%	1.019	0.156	-0.051	-0.005
	(1.79)	(71.21)	(11.3)	(-1.67)	(0.14)	(1.87)	(87.89)	(7.02)	(-2.71)	(-0.26)
Bottom	0.003%	1.034	0.249	-0.069	0.002	-0.016%	1.038	0.112	-0.120	-0.011
	(0.08)	(59.36)	(13.05)	(-2.38)	(0.1)	(-0.31)	(47.18)	(4.64)	(-3.58)	(-0.5)
Top-Bottom	0.062%	-0.018	0.002	0.022	0.001	0.099%	-0.019	0.044	0.069	0.006
	(3.83)***	(-3.19)***	(0.11)	(3.06)***	(0.2)	(2.18)**	(-1.11)	(1.73)*	(2.68)***	(0.81)
6-month										
	Equal-weighted					Value-weighted				
Top	0.071%	1.015	0.247	-0.054	0.000	0.087%	1.020	0.153	-0.055	-0.011
	(1.92)	(76.75)	(12.04)	(-2.06)	(0.03)	(2.17)	(84.54)	(7.72)	(-2.85)	(-0.52)
Bottom	0.004%	1.032	0.244	-0.077	-0.005	-0.019%	1.037	0.111	-0.121	-0.019
	(0.08)	(58.25)	(13.42)	(-2.67)	(-0.33)	(-0.36)	(46.11)	(4.96)	(-3.59)	(-0.92)
Top-Bottom	0.068%	-0.017	0.003	0.023	0.006	0.105%	-0.017	0.042	0.066	0.008
	(3.8)***	(-2.56)***	(0.18)	(3.17)***	(1.37)	(2.43)**	(-0.94)	(1.8)*	(2.69)***	(1.15)
12-month										
	Equal-weighted					Value-weighted				
Top	0.066%	1.017	0.243	-0.056	-0.001	0.073%	1.023	0.152	-0.054	-0.008
	(1.75)	(73.26)	(12.36)	(-2.03)	(-0.03)	(1.85)	(75.06)	(8.34)	(-2.39)	(-0.37)
Bottom	0.004%	1.033	0.234	-0.076	-0.009	-0.020%	1.034	0.104	-0.108	-0.025
	(0.09)	(57.52)	(13.65)	(-2.78)	(-0.63)	(-0.39)	(47.6)	(5.56)	(-3.31)	(-1.47)
Top-Bottom	0.062%	-0.016	0.009	0.021	0.009	0.094%	-0.011	0.048	0.053	0.016
	(3.09)***	(-2.57)**	(0.62)	(3.02)***	(1.93)*	(2.3)	(-0.69)	(2.92)***	(2.75)***	(1.94)*

Table 4-13 (continued)
24-month

	Equal-weighted					Value-weighted				
Top	0.026%	1.021	0.246	-0.073	-0.005	0.025%	1.030	0.152	-0.082	-0.012
	(0.72)	(68.49)	(12.29)	(-2.94)	(-0.31)	(0.67)	(62.81)	(7.87)	(-2.81)	(-0.57)
Bottom	-0.017%	1.037	0.232	-0.089	-0.011	-0.045%	1.039	0.101	-0.108	-0.027
	(-0.38)	(61.98)	(13.56)	(-3.42)	(-0.74)	(-0.98)	(54.8)	(6.03)	(-3.66)	(-1.41)
Top-Bottom	0.043%	-0.015	0.014	0.016	0.007	0.070%	-0.009	0.051	0.026	0.015
	(2.71)***	(-4.47)***	(1.22)	(3.22)***	(2.35)**	(3.1)***	(-1.09)	(4.64)***	(2.98)***	(2.91)***

In Table 4-13, I report risk-adjusted alpha and risk loadings from fund portfolios' excess returns. The top decile indicates funds with the highest SDR, while the bottom decile suggests funds with the lowest SDR. Then, I construct a long-short portfolio by longing funds in the top decile and shorting funds in the bottom decile. In Panel A, in the 1-3 month holding period, consistent with Hypothesis Two (H2), a long-short spread portfolio generates a significant and positive four-factor alpha which ranges from 6.49 (t=3.98) basis points per month (or 77.88 basis points per year) to 9.54 (t=2.28) basis points per month (or 114.48 basis point per year) in a 3-month holding period. Moreover, the equal-weighted portfolio under a 6-month holding period generates a four-factor alpha of 7.09 (t=3.94) basis point (or 85.08 basis points per year) and the value-weighted portfolio generates a four-factor alpha of 10.15 (t=2.33) basis points (or 121.8 basis points per year). It shows decreasing returns from a 6-month holding period to a 24-month holding period with an equal-weighted four-factor alpha of 4.64 (t=2.89) basis points (or 55.68 basis points per year) and a value-weighted four-factor alpha 6.56 (t=2.9) basis points (or 78.72 basis points per year), which suggest that the predictive power of SDR for fund performance is stronger in the short term. In Panel B, I apply the gross return which does not adjust net expenses in the return calculation. The result is similar to that in Panel A. In a 3-month holding period, the long-short spread portfolio produces a significant and positive four-factor alpha that ranges from 6.2 (t=3.83) basis points per month (or 74.4 basis points per year) to 9.9 (t=2.18) basis points (or 118.8 basis points per year). In sum, the results confirm that SDR does have the ability to predict superior fund performance. It implies that sophisticated investors rely less on the performance-based factors and they put more weight on fundamental fund characteristics in their decision mechanism.

4.7.2.2 **Sources of the Return Predictability of SDR**

To examine the sources of the predictive power of SDR for future fund performance, I conduct three subsample analyses based on investor sophistication, scale-decreasing returns and participation costs. First, I use the distribution channel to split the sample into whether fund shares are broker-sold or direct-sold. I take subsamples, depending on whether a fund is institutional or retail, and if its turnover is above the median across sample funds in each year. Second, I take subsamples depending on whether a fund's size is larger than the median level across funds in each month, if it is solo-managed or co-managed, and if fund managers hold their fund shares or not. Third, I partition the samples depending on whether expense ratio, fund family size and volatility are higher than the median level across funds in each month. The results of these robustness tests support the main finding in Table 4-13 that SDR can positively predict future fund performance.

Table 4-14 SDR and Fund Performance: The Sources of Return Predictability

This table reports the abnormal returns of fund portfolios under different investor sophistication, scale-decreasing factors and participation costs. For each month from 2004 to 2016, I sort funds into five portfolios based on their SDR, defined as characteristics R-squared divided by exotic performance R-squared based on fund flows. Following Jegadeesh and Titman (1993), the portfolio is rebalanced every month and held for three months. Equal-weighted and value-weighted average returns across the portfolios in each month are adjusted with the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5) by regressing the excess returns of the monthly portfolio on the returns of risk factors. Top is the fifth quintile portfolio with the highest SDR, bottom is the first quintile portfolio with the lowest SDR, and Top-Bottom (T-B) is a spread portfolio that buys the fifth quintile portfolio and shorts the first quintile portfolio. Panel A partitions the sample depending on whether a fund is broker-sold or direct-sold to investors, if the fund is institutional or retail, and if the fund's turnover is above the median across funds in each month. Panel B partitions the sample depending on whether a fund is larger than the median size across funds in each month, if the fund is solo-managed or co-managed, and if the fund is held by fund managers or not. Panel C partitions the sample depending on whether the expense ratio, the fund family size and fund prior 12-month volatility are larger than the median in each month. Abnormal returns are reported with *t*-statistics computed as standard errors corrected in Newey-West methods with twelve lags. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Table 4-14 (continued)

Panel A: Investor sophistication

	(1) Broker-sold funds	(2) Direct-sold funds		(3) Institutional funds	(4) Retail funds		(5) High turnover	(6) Low turnover	
				FF4 alpha					
Equal-weighted			Diff.			Diff.			Diff.
Top quintile	-0.113%	-0.040%	-0.073%	-0.040%	-0.085%	0.045%	-0.073%	-0.026%	-0.047%
	(-2.19)	(-1.29)	(-2.13)	(-1.17)	(-2.99)	(2.35)	(-1.77)	(-1)	(-1.66)
Bottom quintile	-0.101%	-0.083%	-0.019%	-0.070%	-0.134%	0.063%	-0.104%	-0.063%	-0.042%
	(-2.09)	(-2.08)	(-0.44)	(-1.85)	(-3.03)	(3.19)	(-2.24)	(-1.73)	(-1.27)
T-B	-0.012%	0.043%	-0.054%	0.031%	0.049%	-0.018%	0.031%	0.036%	-0.005%
	(-0.24)	(2.26)**	(-0.88)	(1.97)*	(1.75)*	(-0.61)	(1.61)	(2.17)**	(-0.23)
Value-weighted			Diff.			Diff.			Diff.
Top quintile	-0.129%	0.005%	-0.134%	-0.021%	-0.046%	0.025%	-0.057%	0.007%	-0.064%
	(-3.27)	(0.14)	(-3.58)	(-0.63)	(-0.88)	(0.62)	(-1.29)	(0.19)	(-1.72)
Bottom quintile	-0.156%	-0.055%	-0.101%	-0.092%	-0.067%	-0.025%	-0.088%	-0.064%	-0.023%
	(-3.27)	(-1.23)	(-2.03)	(-2.39)	(-1.26)	(-0.61)	(-1.55)	(-1.57)	(-0.54)
T-B	0.028%	0.061%	-0.033%	0.071%	0.021%	0.050%	0.031%	0.071%	-0.040%
	(0.58)	(1.53)	(-0.45)	(2.72)***	(0.36)	(0.81)	(0.83)	(1.71)*	(-0.79)

	Broker-sold funds	Direct-sold funds		Institutional funds	Retail funds		High turnover	Low turnover	
				FF5 alpha					
Equal-weighted			Diff.			Diff.			Diff.
Top quintile	-0.102%	-0.030%	-0.072%	-0.028%	-0.084%	0.056%	-0.042%	-0.039%	-0.003%
	(-2.13)	(-1.16)	(-2.01)	(-0.97)	(-3.49)	(2.71)	(-1.19)	(-1.68)	(-0.14)
Bottom quintile	-0.088%	-0.068%	-0.020%	-0.059%	-0.113%	0.054%	-0.065%	-0.071%	0.006%
	(-2.15)	(-1.91)	(-0.56)	(-1.77)	(-2.9)	(3.09)	(-1.59)	(-2.01)	(0.16)
T-B	-0.014%	0.038%	-0.051%	0.031%	0.028%	0.002%	0.023%	0.032%	-0.009%
	(-0.3)	(2.23)**	(-0.9)	(2.2)**	(1)	(0.07)	(1.3)	(1.62)	(-0.33)
Value-weighted			Diff.			Diff.			Diff.
Top quintile	-0.125%	0.017%	-0.142%	-0.013%	-0.030%	0.016%	-0.024%	0.004%	-0.028%
	(-3.75)	(0.53)	(-3.95)	(-0.48)	(-0.64)	(0.41)	(-0.67)	(0.12)	(-0.91)
Bottom quintile	-0.137%	-0.036%	-0.101%	-0.078%	-0.033%	-0.045%	-0.052%	-0.052%	0.000%
	(-3.42)	(-0.93)	(-2.35)	(-2.27)	(-0.68)	(-0.99)	(-1.11)	(-1.36)	(0)
T-B	0.011%	0.053%	-0.042%	0.064%	0.004%	0.061%	0.027%	0.055%	-0.028%
	(0.25)	(1.3)	(-0.58)	(2.39)**	(0.05)	(0.9)	(0.83)	(1.31)	(-0.59)

Table 4-14 (continued)

Panel B: Scale-decreasing returns

	(7) Large funds	(8) Small funds		(9) Solo-managed funds	(10) Co-managed funds		(11) Held by managers	(12) Not held by managers	
				FF4 alpha					
Equal-weighted			Diff.			Diff.			Diff.
Top quintile	-0.029%	-0.072%	0.043%	-0.107%	-0.014%	-0.093%	-0.053%	-0.042%	-0.011%
	(-0.89)	(-2.19)	(2.5)	(-3.09)	(-0.43)	(-5.18)	(-1.62)	(-1.1)	(-0.57)
Bottom quintile	-0.094%	-0.081%	-0.012%	-0.136%	-0.057%	-0.079%	-0.088%	-0.072%	-0.016%
	(-2.33)	(-1.96)	(-0.46)	(-3.21)	(-1.48)	(-3.88)	(-2.32)	(-1.48)	(-0.71)
T-B	0.064%	0.009%	0.055%	0.029%	0.043%	-0.014%	0.035%	0.030%	0.005%
	(3.44)***	(0.48)	(2.06)**	(1.26)	(3.37)***	(-0.58)	(2.12)**	(1.2)	(0.16)
Value-weighted			Diff.			Diff.			Diff.
Top quintile	-0.020%	-0.055%	0.036%	-0.029%	-0.014%	-0.015%	-0.023%	0.016%	-0.040%
	(-0.56)	(-1.62)	(1.69)	(-0.84)	(-0.31)	(-0.35)	(-0.67)	(0.32)	(-1.06)
Bottom quintile	-0.076%	-0.054%	-0.022%	-0.083%	-0.070%	-0.014%	-0.074%	-0.088%	0.014%
	(-1.67)	(-1.26)	(-0.63)	(-1.51)	(-1.57)	(-0.33)	(-1.71)	(-1.81)	(0.45)
T-B	0.056%	-0.001%	0.057%	0.055%	0.056%	-0.001%	0.051%	0.104%	-0.053%
	(1.69)*	(-0.05)	(1.62)	(1.18)	(1.5)	(-0.02)	(1.49)	(2.84)***	(-1.26)

	Large funds	Small funds		Solo-managed funds	Co-managed funds		Held by managers	Not held by managers	
				FF5 alpha					
Equal-weighted			Diff.			Diff.			Diff.
Top quintile	-0.021%	-0.061%	0.040%	-0.089%	-0.010%	-0.080%	-0.046%	-0.029%	-0.017%
	(-0.83)	(-2.12)	(2.62)	(-3.19)	(-0.33)	(-4.43)	(-1.63)	(-0.79)	(-0.67)
Bottom quintile	-0.074%	-0.070%	-0.004%	-0.116%	-0.045%	-0.071%	-0.074%	-0.050%	-0.024%
	(-2.18)	(-1.81)	(-0.16)	(-2.97)	(-1.31)	(-2.93)	(-2.17)	(-1.12)	(-0.93)
T-B	0.053%	0.009%	0.044%	0.027%	0.036%	-0.009%	0.028%	0.021%	0.007%
	(3.33)***	(0.46)	(1.83)*	(1.09)	(3.06)***	(-0.32)	(1.84)*	(0.72)	(0.19)
Value-weighted			Diff.			Diff.			Diff.
Top quintile	-0.013%	-0.039%	0.026%	0.000%	-0.011%	0.011%	-0.018%	0.021%	-0.039%
	(-0.44)	(-1.28)	(1.04)	(-0.01)	(-0.29)	(0.25)	(-0.6)	(0.47)	(-1.02)
Bottom quintile	-0.047%	-0.044%	-0.002%	-0.063%	-0.041%	-0.021%	-0.050%	-0.075%	0.025%
	(-1.2)	(-1.1)	(-0.07)	(-1.36)	(-1.11)	(-0.67)	(-1.35)	(-1.79)	(0.87)
T-B	0.034%	0.005%	0.028%	0.062%	0.030%	0.032%	0.032%	0.096%	-0.064%
	(0.93)	(0.21)	(0.74)	(1.31)	(0.87)	(0.62)	(1)	(1.99)**	(-1.4)

Table 4-14 (continued)

Panel C: Participation costs

	(13) High fees	(14) Low fees		(15) Large fund family	(16) Small fund family		(5) Old funds	(6) Young funds	
				FF4 alpha					
Equal-weighted			Diff.			Diff.			Diff.
Top quintile	-0.055%	-0.049%	-0.006%	-0.032%	-0.068%	0.036%	-0.022%	-0.081%	0.058%
	(-1.51)	(-1.71)	(-0.35)	(-0.89)	(-2.12)	(1.66)	(-0.59)	(-2.58)	(1.94)
Bottom quintile	-0.092%	-0.083%	-0.009%	-0.053%	-0.120%	0.066%	-0.084%	-0.084%	0.000%
	(-1.95)	(-2.67)	(-0.31)	(-1.22)	(-3.25)	(2.38)	(-2.45)	(-1.78)	(-0.01)
T-B	0.036%	0.034%	0.002%	0.021%	0.052%	-0.031%	0.061%	0.003%	0.058%
	(1.87)*	(2.21)**	(0.1)	(1.23)	(2.68)***	(-1.2)	(3.57)***	(0.1)	(1.5)
Value-weighted			Diff.			Diff.			Diff.
Top quintile	-0.041%	-0.009%	-0.031%	-0.014%	-0.016%	0.002%	0.002%	-0.059%	0.062%
	(-0.94)	(-0.27)	(-1.18)	(-0.4)	(-0.43)	(0.06)	(0.06)	(-1.5)	(1.98)
Bottom quintile	-0.158%	-0.056%	-0.102%	-0.051%	-0.153%	0.103%	-0.074%	-0.076%	0.002%
	(-2.85)	(-1.31)	(-2.34)	(-1.09)	(-3.2)	(2.29)	(-1.76)	(-1.32)	(0.06)
T-B	0.117%	0.047%	0.070%	0.036%	0.137%	-0.101%	0.076%	0.017%	0.059%
	(3.18)***	(1.33)	(1.58)	(1.07)	(2.77)***	(-2.29)**	(2.02)**	(0.34)	(1.1)

	High fees	Low fees		Large fund family	Small fund family		Old funds	Young funds	
				FF5 alpha					
Equal-weighted			Diff.			Diff.			Diff.
Top quintile	-0.048%	-0.038%	-0.010%	-0.016%	-0.067%	0.051%	-0.015%	-0.069%	0.054%
	(-1.42)	(-1.74)	(-0.51)	(-0.52)	(-2.45)	(2.62)	(-0.49)	(-2.47)	(2.41)
Bottom quintile	-0.077%	-0.069%	-0.008%	-0.042%	-0.101%	0.059%	-0.076%	-0.062%	-0.013%
	(-1.77)	(-2.6)	(-0.29)	(-1.11)	(-3.11)	(2.63)	(-2.42)	(-1.43)	(-0.46)
T-B	0.029%	0.031%	-0.001%	0.027%	0.034%	-0.008%	0.061%	-0.006%	0.067%
	(1.62)	(1.95)**	(-0.05)	(1.59)	(2.05)**	(-0.33)	(3.06)***	(-0.21)	(1.63)
Value-weighted			Diff.			Diff.			Diff.
Top quintile	-0.031%	-0.002%	-0.028%	-0.005%	-0.025%	0.021%	0.012%	-0.047%	0.059%
	(-0.73)	(-0.09)	(-1.02)	(-0.15)	(-0.87)	(0.93)	(0.4)	(-1.35)	(2.07)
Bottom quintile	-0.138%	-0.035%	-0.103%	-0.028%	-0.132%	0.105%	-0.055%	-0.039%	-0.016%
	(-2.84)	(-0.92)	(-2.28)	(-0.69)	(-3.4)	(2.48)	(-1.42)	(-0.83)	(-0.4)
T-B	0.107%	0.032%	0.075%	0.023%	0.107%	-0.084%	0.067%	-0.008%	0.076%
	(3.78)***	(0.86)	(1.68)*	(0.65)	(2.82)***	(-2.21)**	(1.63)	(-0.18)	(1.28)

4.7.2.2.1 Investor Sophistication

Bergstresser, Chalmers and Tufano (2009) find that direct-sold funds outperform broker-sold funds, which offer investors higher risk-adjusted returns. Direct-sold funds show more skills than broker-sold funds in asset allocation on an aggregate level. Moreover, Del Guercio and Reuter (2013) find that direct-sold funds have more incentive to generate alphas and outperform index funds, while broker-sold funds have less incentive to generate alphas and tend to underperform. They also document that investors in direct-sold funds are sensitive to risk-adjusted alphas, while investors in broker-sold funds are sensitive to raw returns. Furthermore, Christoffersen, Evans and Musto (2013) find that fund inflows are significantly affected by funds' payments to brokers. Payments to brokers can skew brokers' incentives and predict poor future fund performance. With evidence from the literature, I, therefore, expect the SDR of direct-sold funds to be more effective in predicting fund performance than that of broker-sold funds. Following Sun (2014), I identify a broker fund that if it has 75% or more of its assets, charges a front-end load or a back-end load, or charges a 12b-1 fee that is larger than 25 basis points on average across share classes. In Table 4-14 Panel A, I sort two subsamples of broker-sold funds and direct-sold funds into five quintiles based on their SDRs. The top SDR quintile of direct-sold funds shows a 0.043% (t=2.26) higher equal-weighted four-factor alpha and a 0.038% (t=2.23) equal-weighted five-factor alpha than the bottom SDR quintile. While in the broker-sold funds, the alphas of the long-short spreads are insignificant at the 10% level, which indicates that SDR is more effective for direct-sold funds and direct-sold investors may be more sophisticated in their fund allocations.

Institutional investors might rely more on advanced methods to select funds. Keswani and Stolin (2006) find that the buying behaviour of both institutional and individual investors causes smart money effect. Ivković and Weisbenner (2009) find that, with tax motivations, individual investors are reluctant to sell well-performing funds, but they are willing to sell under-performing funds. In addition, they find that individual inflows chase the relative performance to other funds, while individual outflows are determined by absolute one-year returns. I identify a fund as institutional if its share-class type contains the label "Inst" from the Morningstar direct database. From Columns 3 and 4 in Panel A Table 4-14, the long-short spread based on SDR of institutional funds shows a positive and significant four-factor alpha ranging from 0.031% (t=1.97) to 0.071% (t=2.72). It also provides a five-factor alpha ranging from 0.031% (t=2.2) to 0.064% (t=2.39). All the alphas of the long-short SDR spreads of retail funds are positive but insignificant at the 5% level. It suggests that institutional funds' SDRs are enhanced predictors of future performance. Consistent with Barber, Huang and Odean (2016), sophisticated institutional investors use advanced benchmarks to evaluate funds.

Ben-Rephael, Kandel and Wohl (2012) apply the net exchange between equity funds and bond funds to measure investor sentiment; they argue that mutual fund flows can measure "noise" in an aggregate market. Stambaugh, Yu and Yuan (2011) document that anomaly returns are stronger during high-level sentiment periods (Baker and Wurgler, 2006). Especially, the short legs of anomalies are more profitable. I employ fund's annual turnover as a sentiment measure and expect that investors will be more rational in lower turnover funds. I identify higher turnover funds as funds that have a monthly turnover above the median across funds. From Columns 5 and 6 of Panel A in Table 4-14, consistent with expectations, I find that the long-short spread of SDR on lower turnover funds has a more significant and positive alpha. It has a four-factor alpha ranging from 0.036% (t=2.17) to 0.071% (t=1.71).

In summary, the results of the robustness test based on investor sophistication are consistent with the main finding in Table 4-13, that SDR is positively associated with future fund performance.

4.7.2.2.2 Scale-Decreasing Returns

In this section, I test whether the performance predictability of SDR is affected by scale-decreasing returns. I hypothesize that investors might be aware of certain factors, including fund total net assets, organizational costs and manager ownership, that induce scale-decreasing returns (Chen et al., 2004; Pollet and Wilson, 2008). I measure organizational diseconomies with a dummy to differentiate solo-managed and co-managed firms.

From Columns 7 and 8 Panel B in Table 4-14, I find that the alpha of the long-short SDR spread of the fund portfolio is significant and positive for large funds, providing a four-factor alpha ranging from 0.064% (t=3.44) to 0.056% (t=1.69), while the alphas of SDR spreads for small funds are all positive but insignificant at the 10% level. Consistent with Chen et al. (2004), since large funds suffer less from liquidity costs, the SDR of large funds is more predictive of future fund performance. It indicates that investors' SDRs in small funds might be not informative about future performance. Investors' decisions based on fundamental fund characteristics are more pronounced for large funds. It may be attributable that large funds have better liquidity. In contrast, small funds are more likely to suffer from liquidity problems and asset fire sales, which may make their SDR less effective in predicting better fund performance.

Bär, Kempf and Ruenzi (2010) find that co-managed funds have less extreme investment styles, more industry diversified portfolios and tend to have less extreme performance. They document that the difference seems to be more pronounced for large teams than small teams. Han, Noe and Rebello (2017) find that co-managed funds perform better, deviate less from their benchmarks and trade less when new information arrives. The investment strategies of co-managed funds are more conservative than solo-managed funds. From Columns 9 and 10 of Table 4-14 Panel B, the spread of solo-managed funds has an equal-weighted four-factor alpha of 0.029% (t=1.26) and an equal-weighted five-factor alpha of 0.055% (t=1.18), while the co-managed fund have an equal-weighted four-factor alpha 0.043% (t=3.37) and an equal-weighted five-factor alpha 0.036% (t=3.06). For solo-managed funds, the alpha of the long-short spread is positive but insignificant at the 10% level. It suggests that SDR is more able to predict performance for co-managed funds than solo-managed funds. Consistent with Han, Noe and Rebello (2017), co-managed funds may have more sophisticated investors with information that is predictive of future fund performance.

From Table 4-14 Panel B Columns 11 and 12, the long-short spread of manager owned funds has an equal-weighted four-factor alpha of 0.035% (t=2.12) and an equal-weighted five-factor alpha of 0.028% (t=1.84). While for funds not held by managers, it has a value-weighted four-factor alpha of 0.104% (t=2.84) and a value-weighted five-factor alpha 0.096% (t=1.99). It indicates that the return predictability of SDR is also affected by manager ownership. The return predictability of SDR might be more pronounced in small funds with manager ownership and large funds without manager ownership.

To sum up, the results of the robustness tests based on potential factors of scale-decreasing return are consistent with the main finding in Table 4-13 that SDR shows predictability for future fund performance.

4.7.2.2.3 Participation Costs

Participation costs might also affect the fund decisions of mutual fund investors. Huang, Wei and Yan (2007) find that investors show different sensitivity to fund performance based on the participation costs of funds. Sirri and Tufano (1998) find that lower search costs can induce higher money flows. In this section, I evaluate the robustness of the performance predictability of SDR with different degrees of search costs and participation costs. I test its robustness given that investors might react differently to a large fund family, high-expense funds and old funds.

From Columns 13 and 14 in Table 4-14 Panel C, funds with higher fees have positive and significant four-factor alphas ranging from 0.036% (t=1.87) to 0.117% (t=3.18). Low fee funds also produce an equal-weighted five-factor alpha of 0.034% (t=2.21). For five-factor alpha, high-fee funds show a stronger value-weighted alpha of 0.107% (t=3.78), while low-fee funds only have an equal-weighted alpha of 0.031% (t=1.95). It suggests that the performance predictability of SDR is more pronounced in high-fee funds.

From Columns 15 and 16, the alpha of the return spread is more significant in small fund families. The spread for small fund families has four-factor alphas ranging from 0.052% (t=2.68) to 0.137% (t=2.77) and five-factor alphas ranging from 0.034% (t=2.05) to 0.107% (t=2.82), while the alpha of the return spread for large fund families has a positive sign but little significance. It suggests that the performance predictability of SDR is more pronounced in small fund families.

From Columns 17 and 18 in Table 4-14, the alpha of the return spread is more significant in old funds. The spread for old fund has four-factor alphas ranging from 0.061% (t=3.57) to 0.076% (t=2.02) and equal-weighted five-factor alphas ranging from 0.061% (t=3.06) to 0.0675 % (t=1.63), while for young funds the alpha of the return spread has a positive sign but is not significant for either four-factor alphas or five-factor alpha. It suggests that the performance predictability of SDR is more pronounced in old funds.

Overall, the results of robustness tests based on participation costs are consistent with the main finding in Table 4-13 that SDR can be utilized as a predictor of superior fund performance.

4.7.2.3 Alternative Risk Measures

Table 4-15 SDR and Fund Performance: Alternative Risk Measures

This table reports the abnormal returns of fund portfolios adjusted with alternative risk measures. For each month from 2004 to 2016, I sort the funds into ten portfolios based on their SDR, defined as characteristics R-squared divided by performance R-squared based on fund flows. Following Jegadeesh and Titman (1993), the portfolio is rebalanced every month and held for three months. The equal-weighted and value-weighted average returns across portfolios in each month are adjusted with the risk free rate, the CAPM , the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5), the Q-factor model (QF) from Hou, Xue and Zhang (2014) and the mispricing-factor model (MF) from Stambaugh and Yuan (2016), by regressing the excess returns of the monthly portfolio on the returns of the risk factors. Top is the tenth decile portfolio with the highest SDR, bottom is the first decile portfolio with the lowest SDR, and Top-Bottom is a spread portfolio that buys the tenth decile portfolio and shorts the first decile portfolio. Panel A takes the net fund return and Panel B takes the gross return to calculate the abnormal returns. Abnormal returns are reported with the *t*-statistics, computed as standard errors corrected in Newey-West methods with twelve lags. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: Net returns

Equal-weighted

SDR deciles	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	QF alpha	MF alpha
Top	0.643%	-0.034%	-0.028%	-0.029%	-0.017%	-0.244%	-0.032%
	(1.64)	(-0.62)	(-0.78)	(-0.81)	(-0.56)	(-6.15)	(-1.12)
Bottom	0.587%	-0.099%	-0.093%	-0.093%	-0.070%	-0.299%	-0.091%
	(1.47)	(-1.69)	(-2.25)	(-2.29)	(-1.95)	(-6.31)	(-2.86)
Top-Bottom	0.056%	0.065%	0.065%	0.065%	0.053%	0.055%	0.059%
	(3.26)***	(4.06)***	(4.05)***	(3.98)***	(3.74)***	(2.86)***	(3.77)***

Table 4-15 (continued)

Value-weighted

SDR deciles	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	QF alpha	MF alpha
Top	0.666%	-0.002%	0.002%	0.003%	0.013%	-0.142%	0.010%
	(1.76)	(-0.04)	(0.04)	(0.07)	(0.35)	(-3.05)	(0.27)
Bottom	0.571%	-0.096%	-0.095%	-0.092%	-0.058%	-0.177%	-0.078%
	(1.43)	(-1.89)	(-1.87)	(-1.81)	(-1.47)	(-4.69)	(-1.98)
Top-Bottom	0.095%	0.094%	0.097%	0.095%	0.072%	0.034%	0.087%
	(2.23)**	(2.08)**	(2.11)**	(2.08)**	(1.7)*	(0.94)	(2.07)**

Panel B: Gross returns

Equal-weighted

SDR deciles	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	QF alpha	MF alpha
Top	0.737%	0.059%	0.066%	0.065%	0.076%	-0.151%	0.062%
	(1.88)	(1.04)	(1.78)	(1.79)	(2.42)	(-3.72)	(2.14)
Bottom	0.685%	-0.002%	0.004%	0.003%	0.026%	-0.203%	0.006%
	(1.71)	(-0.04)	(0.09)	(0.08)	(0.71)	(-4.23)	(0.18)
Top-Bottom	0.053%	0.062%	0.062%	0.062%	0.050%	0.052%	0.056%
	(3.1)***	(3.89)***	(3.9)***	(3.83)***	(3.56)***	(2.73)***	(3.61)***

Value-weighted

SDR deciles	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	QF alpha	MF alpha
Top	0.746%	0.078%	0.082%	0.083%	0.094%	-0.063%	0.090%
	(1.97)	(1.33)	(1.83)	(1.87)	(2.36)	(-1.32)	(2.46)
Bottom	0.648%	-0.020%	-0.019%	-0.016%	0.018%	-0.101%	-0.001%
	(1.62)	(-0.38)	(-0.36)	(-0.31)	(0.44)	(-2.66)	(-0.02)
Top-Bottom	0.099%	0.098%	0.101%	0.099%	0.076%	0.038%	0.091%
	(2.35)**	(2.18)**	(2.22)**	(2.18)**	(1.82)*	(1.05)	(2.17)**

I apply alternative risk measures to adjust the excess returns of a long-short fund portfolio based on SDR. I consider the excess return, the CAPM, the Fama-French three-factor model including market risk, size risk, and value risk; the Q-factor model from Hou, Xue and Zhang (2014) including investment risk (I/A) and profitability risk (ROE); the Fama-French five-factor model including investment risk (CMA) and profitability risk (RMW); the mispricing factors model from Stambaugh and Yuan (2014) including performance-based risk (PERF) and management-based risk (MGMT). The results show findings that SDR positively predicts performances and its predictability is robust with alternative risk adjustments. For the value-weighted portfolio in Panel A, the alpha of the long-short spread of fund net returns under different alternative risk measures in the 3-month holding period is significant and positive, ranging from 0.087% (t=2.07) to 0.097% (t=2.11). In Panel B, by utilizing gross returns, I find that the results are similar to those in Panel A, the value-weighted alpha of the long-short spread ranges from 0.091% (t=2.17) to 0.101% (t=2.22). The results further confirm the performance predictability of SDR under different risk adjustments.

4.7.2.4 Long-Run Performance

Table 4-16 SDR and Fund Performance in the Long Run

This table reports abnormal returns of long-short fund portfolios in the long run. For each month from 2004 to 2016, I sort sample funds into ten portfolios based on SDR, defined as characteristics R-squared divided by performance R-squared based on fund flows. Following Jegadeesh and Titman (1993), the portfolio is rebalanced every month and held for three months to five years. Equal-weighted and value-weighted average returns across portfolios in each month are adjusted with the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5), by regressing the excess returns of the monthly portfolio on the returns of the risk factors. Top is the tenth decile portfolio with the highest SDR, bottom is the first decile portfolio with the lowest SDR, and Top-Bottom is a spread portfolio that buys the tenth decile portfolio and shorts the first decile portfolio. Panel A takes net fund returns and Panel B takes gross returns to calculate abnormal returns. Abnormal returns are reported with *t*-statistics, computed as standard errors corrected in Newey-West methods with twelve lags. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: Net returns

Equal-weighted

SDR deciles	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha
	3-month		6-month		12-month		24-month		36-month		48-month		60-month	
Top	-0.029%	-0.017%	-0.022%	-0.013%	-0.027%	-0.017%	-0.066%	-0.045%	-0.071%	-0.051%	-0.111%	-0.083%	-0.073%	-0.050%
	(-0.81)	(-0.56)	(-0.62)	(-0.42)	(-0.74)	(-0.54)	(-1.83)	(-1.31)	(-1.82)	(-1.39)	(-4.12)	(-2.79)	(-2.03)	(-1.35)
Bottom	-0.093%	-0.070%	-0.093%	-0.074%	-0.092%	-0.067%	-0.112%	-0.076%	-0.112%	-0.078%	-0.159%	-0.115%	-0.112%	-0.077%
	(-2.29)	(-1.95)	(-2.21)	(-1.99)	(-2.05)	(-1.68)	(-2.58)	(-1.84)	(-2.28)	(-1.74)	(-4.59)	(-3.19)	(-2.41)	(-1.67)
Top-Bottom	0.065%	0.053%	0.071%	0.061%	0.065%	0.049%	0.046%	0.032%	0.042%	0.027%	0.048%	0.031%	0.039%	0.027%
	(3.98)***	(3.74)***	(3.94)***	(4.22)***	(3.23)***	(3.12)***	(2.89)***	(2.21)**	(2.43)**	(1.82)*	(2.93)***	(2.17)**	(2.2)**	(1.79)*

Table 4-16 (continued)

Value-weighted

SDR deciles	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha
	3-month		6-month		12-month		24-month		36-month		48-month		60-month	
Top	0.003%	0.013%	0.006%	0.013%	-0.007%	0.005%	-0.055%	-0.028%	-0.060%	-0.031%	-0.085%	-0.051%	-0.047%	-0.023%
	(0.07)	(0.35)	(0.17)	(0.4)	(-0.18)	(0.16)	(-1.52)	(-0.86)	(-1.6)	(-0.92)	(-2.64)	(-1.56)	(-1.19)	(-0.53)
Bottom	-0.092%	-0.058%	-0.095%	-0.066%	-0.096%	-0.067%	-0.121%	-0.087%	-0.106%	-0.074%	-0.127%	-0.080%	-0.083%	-0.041%
	(-1.81)	(-1.47)	(-1.87)	(-1.67)	(-1.86)	(-1.68)	(-2.63)	(-2.25)	(-2.06)	(-1.7)	(-2.88)	(-1.95)	(-1.57)	(-0.8)
Top-Bottom	0.095%	0.072%	0.102%	0.079%	0.090%	0.072%	0.066%	0.059%	0.045%	0.042%	0.042%	0.029%	0.035%	0.018%
	(2.08)**	(1.7)*	(2.33)**	(2.12)**	(2.19)**	(2.11)**	(2.9)***	(2.53)*	(2.02)**	(2.04)**	(1.67)*	(1.21)	(1.2)	(0.73)

Panel B: Gross returns

Equal-weighted

SDR deciles	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha
	3-month		6-month		12-month		24-month		36-month		48-month		60-month	
Top	0.065%	0.076%	0.071%	0.080%	0.066%	0.076%	0.026%	0.047%	0.021%	0.041%	-0.020%	0.008%	0.017%	0.040%
	(1.79)	(2.42)	(1.92)	(2.49)	(1.75)	(2.28)	(0.72)	(1.34)	(0.53)	(1.1)	(-0.72)	(0.25)	(0.47)	(1.05)
Bottom	0.003%	0.026%	0.004%	0.022%	0.004%	0.029%	-0.017%	0.019%	-0.017%	0.017%	-0.065%	-0.020%	-0.018%	0.017%
	(0.08)	(0.71)	(0.08)	(0.59)	(0.09)	(0.72)	(-0.38)	(0.45)	(-0.35)	(0.37)	(-1.86)	(-0.55)	(-0.39)	(0.36)
Top-Bottom	0.062%	0.050%	0.068%	0.058%	0.062%	0.046%	0.043%	0.028%	0.038%	0.024%	0.045%	0.028%	0.035%	0.023%
	(3.83)***	(3.56)***	(3.8)***	(4.03)***	(3.09)***	(2.95)***	(2.71)***	(1.99)**	(2.24)**	(1.61)	(2.71)***	(1.94)*	(1.96)*	(1.54)

Table 4-16 (continued)

Value-weighted

SDR deciles	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha	FF4 alpha	FF5 alpha
	3-month		6-month		12-month		24-month		36-month		48-month		60-month	
Top	0.083%	0.094%	0.087%	0.093%	0.073%	0.085%	0.025%	0.051%	0.019%	0.048%	-0.006%	0.027%	0.030%	0.055%
	(1.87)	(2.36)	(2.17)	(2.74)	(1.85)	(2.51)	(0.67)	(1.54)	(0.5)	(1.36)	(-0.19)	(0.81)	(0.74)	(1.24)
Bottom	-0.016%	0.018%	-0.019%	0.011%	-0.020%	0.009%	-0.045%	-0.012%	-0.031%	0.001%	-0.052%	-0.005%	-0.009%	0.033%
	(-0.31)	(0.44)	(-0.36)	(0.27)	(-0.39)	(0.21)	(-0.98)	(-0.3)	(-0.6)	(0.03)	(-1.2)	(-0.12)	(-0.17)	(0.63)
Top-Bottom	0.099%	0.076%	0.105%	0.083%	0.094%	0.077%	0.070%	0.063%	0.050%	0.046%	0.046%	0.032%	0.039%	0.022%
	(2.18)**	(1.82)*	(2.43)**	(2.24)**	(2.3)**	(2.23)**	(3.1)***	(2.7)***	(2.25)**	(2.28)**	(1.86)*	(1.4)	(1.32)	(0.88)

If investors react to new information with a delay or if they have long-term goals for their investments, I then consider extended horizon periods for SDR spread portfolios. To test the robustness of SDR in the long run, I consider different holding periods from three months to five years. In each month, I sort funds into ten decile portfolios based on their SDRs; then I calculate a long-short spread by longing the funds with the highest SDR and shorting the funds with the lowest SDR. In Table 4-16, I find that the alphas of the spread portfolios are significant and positive during a two-year period for both equal-weighted and value-weighted portfolios. For the four-factor alphas of spread portfolios over a 24-month horizon, they range from 0.046% (t=2.89) to 0.066% (t=2.9). The alphas of the equal-weighted spread portfolio remain significantly positive in the 3-year to 5-year holding periods with four-factor alphas ranging from 0.042% (t=2.43) to 0.039% (t=2.2). For the value-weighted fund portfolio, the alphas are all positive, but their significances decrease from three years to five years. In Panel B, the gross return portfolios show similar results to Panel A, as the long-short spread during the 2-year period has four-factor alphas ranging from 0.043% (t=2.71) to 0.07% (t=3.1), while its significance decreases from 3- to 5-year holding periods. The results further confirm the performance predictability of SDR in the long run.

4.7.2.5 Fama-Macbeth Regression Evidence

To further examine the cross-sectional return predictability of SDR, I utilize the Fama and Macbeth (1973) method and run regressions of fund performance on SDR and control variables. For each month, I estimate the following regression:

$$Perfmance_{I,t+1} = \alpha + \beta_1 SDR_{i,t} + \gamma \mathrm{X}_{i,t} + \varepsilon_{i,t+1}$$

(Eq. 4-11)

Where $Perfmance_{I,t+1}$ is the risk-adjusted performance for fund *i* in month *t*+1, SDR is the Smart-to-Dumb Ratio of fund *i* in month *t*; $X_{i,t}$ is the vector of control variables including fund size, fund family size, turnover, expense ratio, prior 12-month return volatility, prior 12-month flow volatility, lagged flow and lagged returns. For risk adjustment, I use the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model and the Fama-French five-factor model.

Table 4-17 SDR and Fund Performance: Fama-Macbeth Regression

This table reports the coefficients of SDR for monthly fund performance from Fama-Macbeth regressions (1973). The dependent variables include returns and risk-adjusted alphas for month *t*+1. Risk-adjusted alphas are calculated from the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5) with 60-month rolling window regressions. The main independent variable is monthly SDR in month t. The control variables include log of fund size, log of fund family size, fund turnover, fund age, total expense ratio, prior 12-month return volatility and flow volatility and fund flow. I run double-clustered regressions to get the coefficients. Regarding the regressions, standard errors are corrected using Newey-West methods. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Dependent variable: Performance (%) in month *t*+1

Variables	(1) Return	(2) CAPM alpha	(3) FF3 alpha	(4) FF4 alpha	(5) FF5 alpha
SDR	0.003***	0.003***	0.003***	0.003***	0.002**
	(3.430)	(3.572)	(2.843)	(2.913)	(2.325)
Fund size (log)	-0.022***	-0.014***	-0.016**	-0.013**	-0.012**
	(-3.911)	(-2.703)	(-2.568)	(-2.034)	(-2.063)
Family size (log)	0.017***	0.012***	0.014***	0.013***	0.015***
	(7.664)	(4.384)	(5.345)	(5.298)	(5.456)
Turnover	-0.025	-0.027	-0.038	-0.042	-0.026
	(-0.894)	(-0.946)	(-1.033)	(-1.630)	(-0.805)
Age (month)	0.000	-8.314	0.000	1.152	0.000
	(0.431)	(-0.212)	(0.385)	(0.046)	(0.716)
Expense ratio	-6.563**	-7.328**	-7.682***	-6.357***	-5.920***
	(-1.976)	(-2.567)	(-4.245)	(-3.884)	(-2.699)
Return volatility	3.827	-2.820	-2.506	-1.954	-0.852
	(0.604)	(-0.537)	(-0.953)	(-0.735)	(-0.390)
Flow volatility	0.137	0.158	0.033	0.051	0.059
	(1.275)	(1.152)	(0.378)	(0.588)	(0.728)

Table 4-17 (continued)

Lagged flow	0.425***	0.345**	0.202*	0.218**	0.228**
	(2.694)	(2.255)	(1.918)	(2.153)	(2.266)
Lagged returns	1.845	1.385	2.320	1.950	2.004
	(0.811)	(0.635)	(1.471)	(1.165)	(1.376)
Observations	171580	171580	171580	171580	171580
R-squared	0.2512	0.2228	0.1176	0.1040	0.1010
Adjusted R-squared	0.2435	0.2148	0.1084	0.0948	0.0917

In Table 4-17, I report the coefficients and their *t*-statistics with standard errors adjusted using Newey-West methods with twelve lags. The results are robust both economically and statistically. They show that SDR exhibits positive return predictability for fund risk-adjusted performance. In Column 4, SDR has a positive coefficient of 0.003 (t=2.913). The coefficient is significant at the 1% level. It supports that SDR has predictive power for cross-sectional fund performance. Also, consistent with Chen et al. (2004), fund size shows a negative relationship with fund performance. In Column 3, the log of fund size has a significant coefficient of -0.016 (t=-2.568) at the 1% level. Interestingly, lagged fund flow shows a positive coefficient of 0.218 (t=2.153) for predicting performance in Column 4, which is significant at the 5% level. It suggests that the smart money effect exists and lagged flow is predictive of future fund performance (Gruber, 1996; Lu, 1999; Keswani and Stolin, 2008). The results further confirm the performance predictability of SDR under a Fama-Macbeth regression approach.

4.7.3 SDR and Family Strategies

The fundamental R-squared discussed in the previous section focuses on the individual fund level. In this section, I extend the analysis to fund family level. Nanda, Wang and Zheng (2004) find that higher variation in investment strategies increases the probability of generating a star fund. They find that star funds cause a spillover effect, which attracts greater money flows into star funds and other funds in the same fund family. They argue that a fund family with lower ability utilizes the spillover effect of star funds to attract money inflows by maintaining a higher level of strategy variation. I expect a fund family with funds held by more rational investors to have higher abilities. I aggregate the characteristics across funds to their fund families and obtain 242 distinct fund families from 2004 to 2016. To measure the ability of fund families, I utilize the cross-fund standard deviation of performance (Nanda, Wang and Zheng, 2004). Considering the spillover effect of star funds, lower cross-fund standard deviation indicates higher skills of fund families. Specifically, I run the regression as follows:

$$Cross\ fund\ Stddev_{i,t+1} = \alpha + \beta SDR_{i,t} + \gamma \mathrm{X}_{i,t} + \varepsilon_{i,t+1}$$

(Eq. 4-12)

$Cross\ fund\ Stddev_{i,t+1}$ is the cross-fund standard deviation of the Fama-French three-factor alpha of fund family *i* in month *t*+1; $SDR_{i,t}$ is the size-weighted average SDR of each fund family *i* in month *t*. $\mathrm{X}_{i,t}$ indicates family characteristics including number of funds, family size, mean of fund-level flows, number of load funds that charge a front load, a deferred load, or a 12b-1 fee greater than 0.25% in a fund family. It also includes size-weighted average of Morningstar overall ratings, turnover, fund age, expense ratio, return volatility and returns.

Table 4-18 SDR and Family Strategy

This table shows SDR's impact on fund family strategies (242 fund families). The dependent variable is the standard deviation of the Fama-French three-factor (FF3) alpha across funds in each fund family in month *t*+1. (Nanda, Wang, Zheng, 2004). The independent variables include SDR, number of funds in each fund family, log of fund family size, mean of fund-level flows, number of load funds in each family. Fund-level characteristics including SDR, fund age (month), total expense ratio, annual turnover,prior 12-month return volatility and Morningstar overall rating are weighted by fund size. I run double-clustered regressions to get the coefficients. Decomposed R-squareds (individual R^2 %) calculated with Shapley-own methods are listed for each regression. Regarding the regression, cluster effects are studied with standard errors clustered at both the fund level and the month level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Dependent variable: The cross-fund standard deviation (%) of FF3 alpha

	(1)		(2)		(3)		(4)	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
SDR	-0.017**	7.70	-0.015**	1.57	-0.014**	0.98	-0.013**	0.94
	(-2.341)		(-2.121)		(-2.030)		(-1.969)	
Number of funds	0.014***	80.80	0.009***	16.53	0.006	6.67	0.006	6.58
	(3.564)		(2.797)		(1.402)		(1.443)	
Family size	-0.020	11.51	0.014	4.59	0.015	2.22	0.011	2.00
	(-1.641)		(1.072)		(1.171)		(0.850)	
MS overall rating							0.029	0.56
							(1.509)	
Turnover			0.125***	17.26	0.115**	10.52	0.119***	10.56
			(2.641)		(2.525)		(2.596)	
Age (month)			0.000	2.26	0.000	1.22	0.000	1.32
			(1.350)		(1.259)		(1.507)	
Expense ratio			22.765***	17.49	21.779***	10.56	22.773***	10.76
			(3.728)		(3.352)		(3.416)	
Return volatility			5.039***	40.31	5.608***	29.55	5.632***	29.30
			(3.474)		(3.728)		(3.747)	
Fund return					-2.208***	29.81	-2.216***	29.53
					(-3.300)		(-3.319)	
Flows					-0.203	0.47	-0.275	0.52
					(-1.156)		(-1.521)	
Number of load funds					0.004	8.00	0.004	7.92
					(0.847)		(0.929)	
Intercept	1.428***		0.110		0.088		0.063	
	(5.544)		(0.369)		(0.283)		(0.200)	
Cluster month effects	Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes	
Observations	23,698		23,698		23,698		23,698	
R-squared	0.0105		0.0426		0.0636		0.0644	
Adjusted R-squared	0.0104		0.0423		0.0632		0.0639	

In Table 4-18, I report the coefficients of regressions and individual R-squared of each regressor. Consistent with my expectations, SDR is a significant and negative predictor of cross-fund performance deviation. In Column 3, SDR has a negative and significant coefficient of 0.014% (t=-2.03) at the 5% level. The individual explanatory power ranges from 0.94% to 7.70%. The results indicate that fund family mainly held by more sophisticated investors have a lower variation in their investment strategies across funds. They do not take high-variation strategies to produce star funds or take advantage of spillover effects to attract funds flows. Family-level SDR may provide a measure of the ability of fund families in strategy allocation since high SDR is associated with low variations in investment strategies, which indicates better abilities of fund families.

4.7.4 SDR and Prime Broker Comovement

Since common information delivered to investors spreads across funds that share similar brokers, I further examine how SDR affects prime broker comovement. Chung and Kang (2016) find that prime brokers share common information with their client hedge funds and this causes strong comovement of the performance across funds. In addition, comovement turns out to be contagious during a financial crisis period. Following Chung and Kang (2016), I first construct a "PB index" by taking the equal-weighted return of all sample funds as a broker-level return for each broker in month t. Then, I compute style-level returns as equal-weighted of returns of all sample funds having the same Morningstar category and market-level returns as equal-weighted returns of all sample funds.

First, I partition the sample into five subsets and conduct double–clustered regressions with the same specification in each subsample.

$$R_{i,t} = \alpha_i + \beta_i^{PB} R_t^{PB} + \beta_i^{STY} R_t^{STY} + \beta_i^{MKT} R_t^{MKT} + \varepsilon_{i,t}$$

(Eq. 4-13)

Where $R_{i,t}$ is the monthly net returns of fund *i*, R_t^{PB} is the monthly returns of equal-weighted returns of all brokers that serve fund *i*, R_t^{STY} is the monthly return of the fund's corresponding category, R_t^{MKT} is the monthly return of all sample funds. All the returns are in excess of the monthly risk-free rate measured by the one-month treasury bill.

Second, I conduct the above regression based on Equation 4-13 using 60-month rolling windows. I obtain β_i^{PB} as PB-level comovement. Third, to test the statistical differences of coefficients between high SDR funds and low SDR funds. I construct long-short portfolios of betas based on SDR. Then, I compute equal-weighted and value-weighted prime-broker comovement (PB betas), category betas and market betas of these portfolios.

Table 4-19 SDR and Prime Broker Comovement

This table shows SDR and its impact on prime broker comovement. In Panel A, I first partition the sample into five subsamples based on their SDR quintile ranks. Then, I report the regression coefficients of fund returns on primer broker returns, Morningstar categories returns and market level returns under five decile portfolios. Following Chung and Kang (2016), a prime broker return is defined as the equal average returns of all sample funds that share at least one broker with the fund, Morningstar category returns are equal average returns of all funds that have the same Morningstar category, the market level return is the equal average return of all sample funds. Decomposed R-squareds (individual R^2 %) calculated with Shapley-own methods are listed for each regression. Regarding the regressions, cluster effects are studied with their standard errors clustered at both the fund level and the month level in Panel A. In Panel B, I first regress fund returns on prime broker returns, Morningstar category returns and market level returns using 60-month rolling windows; then I obtain coefficients as prime broker betas, category betas and market level betas. I further sort funds based on their SDRs into five fund portfolios and construct long-short portfolios to calculate beta differences. Then, I report equal-weighted and value-weighted betas of prime broker returns, category returns and market level returns. Betas are reported with *t*-statistics, computed as the standard error corrected using Newey-West methods with twelve lags in Panel B. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Table 4-19 (continued)

Table 4-19 (continued)
Panel A:

SDR quintiles	(1)		(2)		(3)		(4)		(5)	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
Prime broker returns	2.974***	47.84	3.296***	47.91	2.910***	47.64	2.806***	47.71	2.848***	47.62
	(7.337)		(5.896)		(7.126)		(7.307)		(6.391)	
Morningstar categories returns	0.959***	28.23	0.947***	28.11	1.005***	28.53	0.987***	28.42	1.005***	28.55
	(51.614)		(59.813)		(64.235)		(62.001)		(60.938)	
Market level returns	-2.935***	23.93	-3.251***	23.97	-2.918***	23.83	-2.791***	23.87	-2.865***	23.83
	(-7.279)		(-5.829)		(-7.196)		(-7.307)		(-6.470)	
Intercept	0.000		0.000		0.000		0.000**		0.001***	
	(1.261)		(0.693)		(1.410)		(2.559)		(3.760)	
Cluster month effects	Yes		Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes		Yes	
Observations	31,177		31,265		31,263		31,265		31,209	
R-squared	0.9171		0.9252		0.9263		0.9208		0.9280	
Adjusted R-squared	0.917		0.925		0.926		0.921		0.928	

Table 4-19 (continued)

Panel B:

SDR quintiles	PB beta	Category beta Equal-weighted	Market beta	PB beta	Category beta Value-weighted	Market beta
1	2.62	0.96	-2.58	3.87	0.98	-3.85
	(12.01)	(122.16)	(-11.96)	(10.96)	(62.59)	(-10.83)
2	2.45	0.97	-2.43	3.15	1.05	-3.21
	(20.73)	(157.06)	(-20.67)	(16.81)	(70.73)	(-17.53)
3	2.43	0.98	-2.41	3.23	1.05	-3.28
	(20.36)	(207.38)	(-20.5)	(21.96)	(91.36)	(-22.33)
4	2.43	0.96	-2.39	3.56	0.98	-3.55
	(22.69)	(183.33)	(-22.07)	(14.88)	(53.35)	(-14.5)
5	2.16	0.98	-2.14	2.83	1.05	-2.88
	(20.08)	(142.62)	(-19.7)	(12.75)	(92.28)	(-13.05)
(5-1)	-0.47	0.02	0.44	-1.04	0.07	0.97
	(-2.24)**	(1.46)	(2.17)**	(-3.08)***	(3.99)***	(2.89)***

In Table 4-19 Panel A, I find that funds with higher SDRs have lower loadings from their broker-level returns. The coefficient of prime broker returns shows a lower coefficient of 2.848 (t=6.391) under the top SDR quintile than the coefficient of 2.974 (t=7.337) in the bottom SDR quintile. To test statistical differences of coefficients between top SDR and bottom SDR funds, in Panel B, the PB beta spread portfolio shows a negative and significant beta difference of -0.47 (t=-2.24) at the 5% level in the equal-weighted column. It also has a negative and significant beta difference of -1.04 (t=-3.08) at the 1% level in the value-weighted column. It suggests that funds with higher SDR rely less on public information from prime brokers and they may have more private information that is predictive of future performance.

4.7.5 SDR and Morningstar Ratings

From the perspective of how ratings affect fund flows, Jenkinson, Jones and Martinez (2016) find that investment recommendations from fund consultants drive fund flows significantly. However, recommendations do not predict superior performance. They argue that winner managers can attract fund flows with their performance, while underperforming managers rely on investment recommendations to attract money.

As Morningstar ratings are based on performance within fund categories, I examine that if reliance on Morningstar ratings and fundamental fund characteristics or if independently reliance on Morningstar rating can predict better performance. I construct the fundamental and rating R-squared (FRRQ) as the sum of R-squared from fund characteristics and Morningstar ratings divided by exotic fund performance's R-squared. Also, I compute rating R-squared (RRQ) as the decomposed R-squared of Morningstar ratings divided by exotic fund performance's R-squared.

$$FRRQ = \frac{decomposed\ R^2\ from\ fundamentals\ + decomposed\ R^2\ from\ MS\ ratings}{decomposed\ R^2\ from\ \ risk - adjusted\ performance}$$

(Eq. 4-14)

$$RRQ = \frac{decomposed\ R^2\ from\ MS\ ratings}{decomposed\ R^2\ from\ \ risk - adjusted\ performance}$$

(Eq. 4-15)

I conduct Fama-Macbeth Regressions (1973) by regressing fund performance on FRRQ and RRQ respectively with controls including fund size, family size, fund turnover, fund age (month), expense ratio, lagged fund flow, prior 12-month return volatility and flow volatility. The dependent variables are fund return and risk-adjusted returns using the CAPM, the Fama-French model, the Fama-French-Carhart model and the Fama-French five-factor model.

$$Perfmance_{I,t+1} = \alpha + \beta_1 FRRQ_{i,t} + \gamma \mathrm{X}_{i,t} + \varepsilon_{i,t+1}$$

(Eq. 4-16)

$$Perfmance_{I,t+1} = \alpha + \beta_1 RRQ_{i,t} + \gamma \mathrm{X}_{i,t} + \varepsilon_{i,t+1}$$

(Eq. 4-17)

Table 4-20 SDR, Morningstar Ratings and Fund Performance

This table reports the impact of FRRQ (fundamentals and ratings R-squared) and RRQ (rating R-squared) on monthly fund performance. Dependent variables include returns and risk-adjusted alphas for month *t*+1. Risk-adjusted alphas are calculated from the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) with 60-month rolling window regressions. The main independent variables are monthly FRRQ for month t in Panel A and monthly RRQ in Panel B. Control variables include Morningstar 3-year and 5-year ratings, log of fund size, log of fund family size, fund turnover, fund age, total expense ratio, fund flow, prior 12-month return volatility and flow volatility. I run Fama-Macbeth regressions to get the coefficients. Regarding the regressions, standard errors are corrected using Newey-West methods. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Table 4-20 (continued)

Panel A:
Dependent variable: Performance (%) in month *t*+1
(1) Control for fund characteristics

Variables	(1) Return	(2) CAPM alpha	(3) FF3 alpha	(4) FF4 alpha	(5) FF5 alpha
FRRQ	0.002***	0.003***	0.003***	0.003***	0.002**
	(3.230)	(3.245)	(2.722)	(2.680)	(2.226)
Observations	171580	171580	171580	171580	171580
R-squared	0.2512	0.2228	0.1175	0.1040	0.1010
Adjusted R-squared	0.2435	0.2148	0.1084	0.0947	0.0917

(2) Control for fund characteristics and add ratings

Variables	(1) Return	(2) CAPM alpha	(3) FF3 alpha	(4) FF4 alpha	(5) FF5 alpha
FRRQ	0.003***	0.003***	0.003***	0.003***	0.002**
	(3.330)	(3.479)	(2.822)	(3.619)	(2.174)
MS 3-year rating	0.041**	0.032*	0.050**	0.027	0.041**
	(2.036)	(1.771)	(2.484)	(1.279)	(2.331)
MS 5-year rating	0.003	0.027**	-0.008	0.012	-0.004
	(0.243)	(2.260)	(-0.586)	(0.934)	(-0.314)
MS 10-year rating	-0.004	0.006	0.008	0.006	0.006
	(-0.792)	(0.999)	(1.178)	(1.005)	(0.787)
Observations	148071	148071	148071	148071	148071
R-squared	0.272	0.2522	0.1464	0.1295	0.1265
Adjusted R-squared	0.2606	0.2404	0.1329	0.1157	0.1126

Panel B:
Dependent variable: Performance (%) in month *t*+1
(1) Control for fund characteristics

Variables	(1) Return	(2) CAPM alpha	(3) FF3 alpha	(4) FF4 alpha	(5) FF5 alpha
RRQ	-0.000	0.001	0.005	-0.000	0.000
	(-0.016)	(0.112)	(0.451)	(-0.065)	(0.060)
Observations	171580	171580	171580	171580	171580
R-squared	0.2513	0.2228	0.1175	0.1039	0.1011
Adjusted R-squared	0.2436	0.2148	0.1084	0.0946	0.0918

Table 4-20 (continued)
(2) Control for fund characteristics and add ratings

Variables	(1) Return	(2) CAPM alpha	(3) FF3 alpha	(4) FF4 alpha	(5) FF5 alpha
RRQ	0.008	0.011	0.009	0.003	0.007
	(0.719)	(0.924)	(0.877)	(0.397)	(0.702)
MS 3-year rating	0.042**	0.033*	0.051**	0.028	0.042**
	(2.067)	(1.795)	(2.503)	(1.303)	(2.348)
MS 5-year rating	0.003	0.027**	-0.008	0.012	-0.004
	(0.264)	(2.280)	(-0.581)	(0.938)	(-0.312)
MS 10-year rating	-0.005	0.005	0.008	0.006	0.006
	(-0.903)	(0.920)	(1.143)	(0.961)	(0.772)
Observations	148071	148071	148071	148071	148071
R-squared	0.2720	0.2523	0.1463	0.1294	0.1265
Adjusted R-squared	0.2606	0.2404	0.1329	0.1156	0.1127

In Table 4-20, I report the coefficients for the regressions above. In Panel A, I find that a combination of fundamentals and Morningstar ratings still has good predictive power for future performance. In Column 4, with controls for fund characteristics, it shows a significant and positive coefficient of 0.003 (t=2.68) at the 1% level. With controls for rating, it also indicates a significant coefficient of 0.003 (t=3.619) at the 1% level. In Panel B, RRQ shows little significance to predict fund performance. By focusing on Morningstar ratings in both Panels A and B, Morningstar 3-year rating shows some evidence to predict three-factor risk-adjusted alpha (0.05, t=2.484; 0.051, t=2.503), and they have better significance than those of Morningstar 5-year rating and 10-year rating in both Panels A and B. The findings indicate that investors who utilize a combination of fundamental fund characteristics and Morningstar ratings to pick funds can achieve superior performance from the funds they invest in. However, investors merely rely on Morningstar ratings in their fund decisions might not obtain superior performance. It suggests investors might consider Morningstar ratings and fundamental fund characteristics together in their fund selection.

4.7.6 SDR and Anomaly Returns

From the perspective of how fund flows affect anomaly returns, Akbas et al. (2015) find that mutual fund flows appear to be dumb and to exacerbate cross-sectional mispricing, while hedge fund flows tend to be smart and to correct mispricing. They document that mutual funds tend to purchase overvalued stocks and push stock prices to become more overvalued.

Table 4-21 SDR Flows and Anomaly Returns

This table reports the Fama-Macbeth regressions of anomaly returns on aggregate fund flows. I include three anomalies: gross profitability, composite equity issues and return on assets (Stambaugh, Yu and Yuan, 2012). Dependent variables are the long-side returns of these three anomalies. The main independent variables are the aggregate monthly flows of funds under the top decile and bottom decile ranked by SDR. Top is the tenth decile portfolio with the highest SDR; bottom is the first decile portfolio with the lowest SDR. I control for market risk factor (MKT), size risk factor (SMB), value risk factor (HML), aggregate illiquidity factor (AGGILLIQ) from Pástor and Stambaugh (2003) and aggregate turnover (AGGTURN). Coefficients are reported with *t*-statistics computed as standard errors corrected using Newey-West methods with twelve lags. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Table 4-21 (continued)

Dependent variable: Anomaly returns in month *t*+1

Variables	Gross profitability			Composite equity issues			Return on asset		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Top SDR flow	0.0030**	0.0031**	0.0029**	0.0020	0.0021**	0.0018**	0.0028*	0.0029**	0.0027*
	(2.11)	(2.56)	(2.49)	(1.6)	(2.4)	(2.05)	(1.73)	(2.03)	(1.88)
Bottom SDR flow	-0.0005	0.0003	0.0004	-0.0011	-0.0001	-0.0000	-0.0009	-0.0006	-0.0003
	(-0.13)	(0.09)	(0.12)	(-0.21)	(-0.03)	(-0.01)	(-0.19)	(-0.12)	(-0.06)
MKT	0.1673		0.1269	0.1924		0.1447	0.1435		0.1180
	(1.19)		(1.08)	(1.1)		(1.04)	(1.03)		(0.93)
SMB	-0.2593*		-0.2495*	-0.3378**		-0.3261**	-0.3677**		-0.3630**
	(-1.8)		(-1.94)	(-2.01)		(-2.4)	(-2.43)		(-2.55)
HML	-0.1470		-0.1093	0.0127		0.0569	-0.1285		-0.1000
	(-1.26)		(-1.14)	(0.09)		(0.47)	(-1.11)		(-0.92)
AGGILLIQ		0.1811*	0.1655*		0.2131*	0.1952*		0.1247	0.1119
		(1.71)	(1.86)		(1.69)	(1.84)		(1.28)	(1.33)
AGGTURN		0.0047	0.0049		0.0047	0.0057*		0.0036	0.0038
		(1.44)	(1.47)		(1.47)	(1.79)		(1.35)	(1.45)
Intercept	0.0062	-0.0077	-0.0086	0.0064	-0.0074	-0.0109	0.0076	-0.0032	-0.0039
	(1.42)	(-0.8)	(-0.8)	(1.14)	(-0.82)	(-1.04)	(1.55)	(-0.44)	(-0.47)
Observations	155	155	155	155	155	155	155	155	155
R-squared	0.0581	0.0937	0.1207	0.0601	0.0473	0.0872	0.0540	0.0940	0.1279
Adjusted R-squared	0.0265	0.0695	0.0788	0.0286	0.0219	0.0437	0.0223	0.0698	0.0864

To examine whether fund flows are smart in exploiting stock return anomalies in the right direction, I sort the sample funds into ten deciles based on SDR in each month. Then, I compute aggregate mutual fund flows of the top decile fund portfolio with the highest SDR, and aggregate mutual fund flows of the bottom decile with the lowest SDR. I expect the top SDR flow to be smart and to trade in the undervalued stocks, rather than overvalued stocks. As the mutual fund might have constraints in shorting (Gruber, 1999, Boguth and Simutin, 2018), I compute the returns by longing three anomalies based on gross profitability, composite equity issues and return on assets. (Stambaugh, Yu and Yuan, 2012). The strategy of longing on undervalued stocks based on anomalies generates positive returns when the prices of stocks move to their fundamentals, and aggregate mispricing is corrected. I run the regression as follows:

$$Anoamlies\ returns_{\ i,t+1} = \alpha + \beta \sum SDR\ flows_{i,t} + \gamma \mathrm{X}_t + \varepsilon_{i,t+1}$$

(Eq. 4-18)

Where $Anoamlies\ returns_{i,t+1}$ is the long-side return of anomaly *i*, $SDR\ flows_{i,t}$ includes aggregate fund flows of the decile portfolio with the highest (top) SDR and the lowest (bottom) SDR. Control variables include market risk factor, size risk factor, value risk factor, aggregate illiquidity factor (AGGILLIQ) from Pástor and Stambaugh (2003) and aggregate turnover (AGGTURN).

In Table 4-21, I find that aggregate fund flows in the top SDR deciles are positively associated with anomaly returns. One percent of aggregate top SDR flow can significantly predict a 0.0029% (t=2.49) return on gross profitability at the 5% level, 0.0018% (t=2.05) on composite equity issues at the 5% level and 0.0027% (t=1.88) on return on assets at the 10% level. It indicates that higher SDR flows are relative smarter and higher SDR funds may purchase undervalued stocks rather than irrationally pushing them in the opposite direction. It indicates that high SDR funds may have good understandings of stock return anomalies and may target gross profitability, composite equity issues and return on assets. This is consistent with H3 that funds held by more sophisticated investors with higher SDR tend to outperform others.

4.8 Conclusion

This study systematically examines the relative importance of fund flow determinants from risk-adjusted performance, risk beta and non-risk perspectives with a comprehensive dataset comprising the China and US actively managed funds. I examine how investors react to risk factors and non-risk factors using Shapley-Owen R-squared decompositions. This approach allows us to consider the relative importance of flow determinants for investors based on decomposed R-squared.

I find that, first, the CAPM outperforms other risk models in driving fund flows in China. Also, risk factors have a limited role in predicting fund flows, while investors tend to use CAPM alpha rather than beta to assess fund performance in both the China and US markets. Second, non-risk factors, especially fund size, lagged flows and past return volatility, largely explain (73.20% to 83.23%) fund flows in China. Also, non-risk factors, especially lagged flows, fund size and Morningstar ratings have the largest R-squared (89.06% to 91.29%) explaining fund flows in the US. This implies that non-risk factors are more important than risk betas and risk-adjusted alphas. Although investors have some risk concerns in their fund pickings, they are more aware of fundamental fund characteristics in the long run. Third, the success of CAPM might be attributable to the impact of lagged fund flows, fund diversification and return gap in China, but attributable to the impact of smart money and the ability to handle scale-decreasing returns in the US.

In addition, to investigate the performance implications of decomposed R-squared for flow determinants, I propose the Smart-to-Dumb Ratio (SDR) and find that it can distinguish sophisticated investors from performance-chasing ones. SDR is predictive of superior fund performance. A spread portfolio based on SDR generates a four-factor alpha of about 121.8 basis points annually. The predictability power of SDR is robust under different risk measures and sub-period analyses. Moreover, SDR indicates a higher family ability to employ lower variation investment strategies. Furthermore, I find that higher SDR funds indicate more sophisticated investors who might retain advantageous information about superior performance, thus rely less on broker-level common information. Finally, higher SDR flows may be smart money that trades on undervalued stocks based on the stock return anomaly of gross profitability, composite equity issues and return on assets.

The results shed light on the explanations of the success of CAPM in modelling the capital response of Berk and Van Binsbergen (2016) and Baber, Huang and Odean (2016) as non-risk effects exist and non-risk factors significantly drive fund flows with market risk measured by CAPM, while multiple factor models can fit returns, but not fund flows. The explanatory power of non-risk factors is a reason for the failure of risk models to capture fund flows, which provides more explanations for CAPM' success.

Chapter 5 Holding Cash for Better Decisions? A Comparison Study of Cash Management Between China and US Mutual Funds

5.1 Introduction

Cash holdings are an essential component of actively managed mutual funds. Holding cash is costly (Wermers, 2000), but it also provides fund managers with flexibility to accommodate fund flows (Simutin, 2013). As the largest emerging market, China has experienced rapid growth with the industry size increasing from 2.62 billion yuan in 2002 to 274.73 billion yuan in 2016. Interestingly, with relatively higher average cash holdings (12%) in China than the level in the US (close to zero), the mutual fund market in China still performs well, with an average industry return about 8% in the last decade, while the US market provides an average performance close to zero. In addition, in 2015, some equity funds in China changed their names to allocations funds to avoid the 80% equity allocation limits on policies. It indicates that cash holdings that directly reveal the asset allocation proportions of fund managers should be an important signal for investors as this can reflect management skill (Simutin, 2013; Graef et al., 2018).

As Simutin (2013) points out, US equity funds with higher abnormal cash can outperform their peers. However, there is limited understanding of the allocation and application of abnormal cash. In addition, there is a growing body of literature focusing on portfolios of funds (Cremers and Petajisto, 2009; Kacperczyk, Sialm and Zheng, 2005). I identify several research gaps in the existing literature. First, existing literature offers limited discussion on the relative importance of cash determinants. Second, limited studies have been conducted on the risk preferences or investment strategies of funds with higher abnormal cash. Finally, limited studies interactively examine the impact of abnormal cash and fund flows on fund performance. The performance predictability of abnormal cash holdings might be affected by lagged flow or the smart money effect (Gruber, 1996; Zheng, 1999).

Do skilled managers keep more cash? How do fund managers with high abnormal cash holdings invest? Do cash holdings imply superior management skill outside US mutual fund markets? On the one hand, holding cash is costly; 0.7 % of annual US fund underperformance is due to nonstock holdings from 1975 to 1994 (Wermers, 2000). On the other hand, fund managers can benefit from the flexibility of holding cash for investing in new opportunities, accommodating fund flows and controlling for transaction costs (Simutin, 2013). I follow Simutin (2013) and Graef et al. (2018) and define abnormal cash holdings (ACH) as residuals by regressing cash holdings on multiple determinants. R-squared decomposition is applied to examine the relative importance of cash determinants. Then, I conduct multiple regression analysis to detect the investment strategies of high abnormal cash funds towards different risk factors. I further examine the cash-flow relationship and construct long-short fund portfolios to explore the relation between abnormal cash holding and fund performance.

In this study, I examine the perspective of the relative importance of cash determinants and portfolio risk exposure, and seek to understand the influence of abnormal cash holdings on funds. I focus on the trading practices of fund managers with relatively higher cash holdings and compare their impact between China and the US. I obtain a comprehensive dataset comprising China mutual fund data and portfolio holdings data from the CSMAR Chinese mutual fund database. The sample covers 556 actively managed funds in China, from 2004 to 2016. Also, for comparison, I obtain US mutual fund data from Morningstar Direct which covers 2,412 US equity funds.

The main results are summarized as follows. First, non-risk factors such as fund size, fund age and return volatility are essential determinants of cash holdings in China. Specifically, smaller funds, younger funds and higher return volatility funds hold more cash. Fund size, fund age and return volatility explain 14.39%, 14.62% and 19.66% of cash holdings in the next quarter. Also, I find that funds with lower fund-report attention and lower active shares carry more money. Fund-report attention and active shares, respectively, explain 15.56% and 4.18% of cash holdings in China. In contrast, risk factors including market risk, size risk, value risk and momentum risk show relative higher explanatory power than non-risk factors in the US. Funds in smaller families with higher lagged flows and lower market betas hold more cash. Market beta accounts for the most substantial decomposed R-squared at 43.08%, while fund family size and lagged flows also account for 14.21% and 11.29% of the next quarter's cash holdings in the US.

Second, fund managers with higher abnormal cash holdings tend to tilt their portfolios to stocks with higher asset growth and higher profitability in China. While in the US, managers reduce their portfolios' risk loading on market risk, momentum risk, profitability risk, management risk and performance risk. It implies that funds in the US with higher abnormal cash are more conservative and seek to reduce their portfolio risk exposure compared to funds in China.

Third, higher abnormal cash holdings can attract money inflows in both the China and US markets. 1% of abnormal cash holding is related to 0.162% (t=2.435) of fund inflows in China. In addition, in the US, 1% of abnormal cash holding is related to 0.183% (t=2.959) of fund inflows in the next quarter. Sophisticated investors might identify it as a trading signal in their fund selection.

Fourth, abnormal cash holdings can predict fund performance in the US markets. A long-short fund portfolio sorting by abnormal cash holdings generates a monthly three-factor alpha of 0.065% (t=2.02) and a monthly four-factor alpha of 0.06% (t=1.85). Moreover, lagged flow might have a positive impact on abnormal cash holdings in terms of predicting fund performance in the US below the medium flow quintile. US funds with the extreme lagged flows but higher abnormal cash tend to underperform compared to their peers, indicating that there is a tradeoff between more money inflows and the cost of holding cash.

My study contributes to three strands of the literature. First, there is a growing number of researchers studying the determinants of mutual fund cash holdings and liquidity management (Yan, 2006; Simutin, 2013; Hanouna et al., 2015; Graef et al., 2018). Moreover, there is extensive literature studying corporate cash holdings (Opler et al., 1999; Dittmar and Mahrt-Smith, 2007; Fresard, 2010). My results present the relative importance of cash determinants and compare these between China and the US. It suggests that US funds are more risk-averse and influenced more by risk factors such as systematic risk, size risk and value risk than non-risk factors. Especially, systematic risk is essential in determining cash holdings. While Chinese funds are more affected by non-risk factors than risk factors to determine cash.

Second, my study is related to the literature on the risk-taking of mutual fund asset allocations, including Frazzini and Petersen (2014), Christoffersen and Simutin (2017) and Boguth and Simutin (2018). It is also related to the literature studying risk factors in investors' decisions, such as Barber, Huang and Odean (2016), Berk and Van Binsbergen (2016) and Agarwal, Green and Ren (2018). The findings provide empirical support to explicitly understand the sources of abnormal cash holdings and how managers tilt their portfolio. My results suggest that fund managers with higher abnormal cash have different risk incentives in stock selection. Profitability risk and investment risk from the Q-factor model by Hou, Xue and Zhang (2015) appear to be signals for fund managers in China, while systematic risk, momentum risk and mispricing risk appear to be the concerns of US fund managers in future asset allocation.

Finally, I contribute to the extensive literature studying mutual fund performance and smart money effects, including Gruber (1996), Zheng (1999), Wemers (2003), Frazzini and Lamont (2008) and Keswani and Stolin (2008). In my studies, the ability of abnormal cash holding is interactively investigated with lagged flow. Abnormal cash holdings show the different predictive power of fund performance between China and the US. My findings also suggest that lagged flows have a positive impact on abnormal cash holdings under the medium flow level in terms of predicting future fund performance in the US market.

The remainder of the study is organized as follows. Section 5.2 reviews the literature and Section 5.3 proposes hypotheses. Section 5.4 defines the variables and introduces the methodology. Section 5.5 examines the determinants of fund cash holdings. Section 5.6 explores the relation between trading practices and cash holdings. Section 5.7 provides evidence of how investors react to abnormal cash holding. Section 5.8 analyzes abnormal cash and mutual fund performance. Section 5.9 draws conclusions.

5.2 Literature Review of Cash Management

This study fits into the extensive literature studying the cash management of mutual funds. Holding cash is crucial in the liquidity management practices of mutual funds. Earlier literature provides evidence that fund managers hold cash to cover uncertain redemptions (Chordia, 1996); even though fund managers holding cash is costly (Wermers, 2000), funds with less cash do not show superior stock-picking skills. Skilled fund managers with large money inflows consistently hold more cash as they trade infrequently (Yan, 2006). Moreover, fund managers benefit from holding cash to accommodate outflows and cover transaction costs. Simutin (2013) defines an abnormal cash holding as the difference between expected cash and actual cash, which indicates the amount of cash that is higher than the average industry level. Funds with higher abnormal cash holdings outperform their peers with lower abnormal cash holdings by over 2% annually. With a focus on the European market, Graef et al. (2018) confirm that EU funds with higher abnormal cash holdings also outperform their low cash peers. They find that funds' fee structure, past flow, flow volatility and investment strategies determine their cash level. From the perspective of liquidity transformation, Chernenko and Sunderam (2016) find that fund managers prefer to carry substantial cash to cover redemption costs, rather than liquidate their holdings, especially funds with illiquid asset and when market liquidity is low. They also find that cash holdings are affected by the liquidity provisions of traditional banks and the shadow bank sector.

In addition, fund managers might transact at disadvantageous prices if they carry inadequate cash holdings to maintain liquidity. An assessment of managers' skills should consider liquidity-motivated trading as fund underperformance is due to the cost of it (Edelen, 1999). Investors can earn significant premiums by trading against mutual funds in asset fire sales by providing liquidity. Funds without proper liquidity management under massive money outflows or inflows will sell their holdings below their fundamental value or invest more in their existing holdings (Coval and Stafford, 2007). Investors can utilize flow-induced trade by mutual fund managers to earn significant premiums. A previous winner in money flows can utilize new money to drive up the price of their stock holdings, while a loser fund has to sell existing holdings to meet redemptions which drags down the stock price (Lou, 2012). Holding more illiquidity assets or less cash can enhance the flow sensitivity of outflows to the underperformance of corporate bond funds (Goldstein, Jiang and Ng, 2017).

As patient managers trade infrequently and accommodate inflows more efficiently (Yan, 2006; Simutin, 2013), I further investigate the literature regarding the investment strategies that interact with cash management. A strand of literature studies risk (beta) strategies and leverage constraints of mutual funds. Boguth and Simutin (2018) find that higher beta stocks are implicit leverage for mutual fund managers facing constraints to lever up their portfolios. Beta strategies that long lower beta stocks and short higher beta stocks have been found to provide positive and significant returns. (Frazzini and Pedersen, 2014). They find that funds with low-risk exposure outperform their high-risk exposure peers by 5% annually. Karceski (2002) also finds that the return-chasing behaviour of investors across time and funds gives fund managers an incentive to tilt their portfolios towards higher beta stocks. In addition, Christoffersen and Simutin (2017) find that defined-contribution plan sponsors often monitor pension funds relative to benchmarks. To keep funds' tracking errors around their benchmarks, fund managers have the incentive to tilt their portfolio to higher beta stocks and to keep away from low beta stocks. Higher risk-taking is not a proper investment practice for retirement money, which suggests more policy controls for it.

5.3 Hypotheses Development

Fund managers in China generally show higher cash levels (12%) than those of US fund managers (close to zero). Notably, the China fund market generally provides an average total return of over 8%, while the US fund market offers a return close to zero (as shown in Chapter 3). Also, the literature documents that holding too much cash can increase the opportunity costs of investors or drag down fund returns (Wermers, 2000), while it also provides fund managers with the flexibility to cover redemptions or other costs (Chordia, 1996; Simutin, 2013). Based on the statistics and literature above, I study cash holding determinants in China and the US. R-squared decomposition enables us to compare the explanatory power of risk determinants and non-risk determinants. Given that institutional backgrounds differ, I expect risk factors and non-risk factors to have different explanatory power for future cash holdings. Thus, I propose Hypothesis 1:

Hypothesis 1 (Determinant Hypothesis): Fund managers are more affected by non-risk factors to determine their cash holdings than risk factors in China, while it reverses in the US.

The literature documents that funds with abnormal cash tend to have better fund performance than their peers (Simutin, 2013 and Graef et al., 2018). It is natural for investors to ask how fund managers utilize abnormal cash to outperform others. On the one hand, fund managers can cover costs related to fund redemption or other transaction costs. On the other hand, if fund managers identify some new investment opportunities, they can quickly purchase new attractive investment opportunities using cash. Yan (2006) finds that there is a trade-off between the cost of holding cash and the flexibility of holding cash to satisfy redemptions or quickly invest in new attractive stocks. They find that funds with higher money inflows tend to hold more cash since they trade infrequently. In contrast, they find that funds with lower cash holdings do not exhibit superior skill in stock selection. Simutin (2013) finds that cash holdings can reflect stock picking ability and market timing ability. It indicates the ability of fund managers to accommodate fund flows or cover relevant costs in transactions. As fund managers benefit from cash to quickly invest in attractive opportunities, I would expect the future trade of fund managers with abnormal cash to be relatively smart.

Moreover, to detect if the investment strategies of funds with high abnormal cash are smart and informative of fund performance, I focus on the perspective of risk exposures. There is a small but growing strand of literature focusing on portfolio management in the risk (beta) strategies of mutual funds. Boguth and Simutin (2018) find that the average market beta of portfolios can capture the desire for leverage and the tightness of their leverage constraints. Fund managers choose to level up their portfolio beta rather than directly use their leverage due to investment constraints. Consistent with the betting-against-beta literature, funds with low-risk exposure outperform high-exposure funds by 5% per year. With a focus on pension investments, Christoffersen and Simutin (2017) find that fund managers with large defined contribution (DC) assets have an incentive to tilt their portfolios towards high-beta stocks since DC plan sponsors monitor their performance relative to benchmarks which can exacerbate pricing anomalies. DC plan sponsors do not penalize fund managers for selecting high-beta stocks with low or negative alphas as DC fund flows are determined by relative returns rather than alphas or betas.

Motivated by the literature above, I further examine future investment strategies based on the different risk exposures of funds holding abnormal cash. It allows us to understand how abnormal cash affects the future investments of fund managers and why fund managers with higher abnormal cash outperform their peers. Then, I explore how beta-strategies differ in China and the US. I hypothesize that fund managers with higher abnormal cash to reduce their portfolio risk loading from high beta stocks. Thus, I have Hypothesis 2:

Hypothesis 2 (Beta Hypothesis): Fund managers with higher abnormal cash holdings will reduce their portfolio risk exposure (beta) in their future investment strategies.

Investor appears to be sensitive to the cash management of mutual funds and select funds based on their abnormal cash. Simutin (2013) finds that equity funds with higher abnormal cash tend to have better performance. US funds with higher abnormal cash outperform their peers by over 2% annually. Managers benefit from the flexibility of holding cash to invest in new attractive stocks, satisfy money outflows, and control trading costs. Graef et al. (2018) also confirm the return predictability of abnormal cash holdings among European funds. They suggest that abnormal cash should be an important proxy for measuring managers' skill. Zeng (2017) finds that the cash management of mutual funds with illiquid assets can benefit investors with a flexible NAV. Moreover, from the perspective of cash holdings and liquidity management, Goldstein, Jiang and Ng (2017) find that the flow sensitivity of outflows to the poor performance of corporate bond funds is stronger when corporate bond funds have fewer cash holdings or more illiquid assets. Chernenko and Sunderam (2016) find that funds tend to hold substantial cash to accommodate fund subscriptions and redemptions rather than transact their portfolios. The tendency is stronger when they have more illiquid assets and market liquidity is low. They also show that external price impacts cannot be mitigated by the cash holdings they have.

As evidence has been found that abnormal cash holdings are predictive of future fund performance in the US market, I expect skilled fund managers in China to take advantage of the flexibility of abnormal cash holdings, too.

Furthermore, Keswani and Solin (2008) find that the smart money effect exists in the UK, as well as in the US. It is attributed to the buying behaviour of both institutional and individual investors. Zheng (1999) finds that funds with higher past flow subsequently outperform their peers with low flows. The smart money effect is large and short-lived. Momentum strategies can only partially explain it. Importantly, the smart money effect is more pronounced in small funds.

The literature indicates that smart money might have an important link to liquidity management in small funds. Base on the literature above, I further examine how abnormal cash interacts with the smart money effect in predicting fund performance. I expect that sophisticated investors evaluate funds from the perspective of both abnormal cash holdings and the smart money effect in both China and the US. I thus propose Hypothesis 3:

Hypothesis 3 (Performance Hypothesis): Sophisticated investors identify abnormal cash holdings as a signal with lagged flows to predict fund performance.

5.4 Data and Methodology

I obtain quarterly data for equity funds and allocations funds in China from the CSMAR Chinese mutual fund database from 2004 to 2016. To ensure a fund is actively investing in the equities market, I take fund classifications from the Morningstar Direct database under the "Morningstar Category" of "Equity funds, Aggressive Allocation funds and Moderate Allocations funds." I exclude index funds, ETFs and closed-end funds in the sample. For US data, I obtain these from the Morningstar Direct database; I restrict the sample to "U.S. equity funds" defined in Morningstar US category group and study equity funds with their assets under management (AUM) of at least 20 million dollars (Graef et al., 2018). I take abnormal cash holdings as residuals by regressing cash holdings on multiple determinants, following Simutin (2013).

To adjust risk factors for fund returns, I apply the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model, the Fama-French five-factor model and the Q-factor model; I compute risk betas from these models over a rolling horizon of 24 months with monthly return data. Due to data availability, I only compute the mispricing factor model from Stambaugh and Yuan (2015) in the US market.

To control for alternative indicators of management skills, I calculate fund diversification (Pollet and Wilson, 2008), industry concentration index (Kacperczyk, Sialm and Zheng, 2005), reliance on public information (Kacperczyk and Seru, 2007), active share (Cremers and Petajisto, 2009) and return gap (Kacperczyk, Sialm and Zheng, 2008) for each fund in quarter t. For China, the final sample contains 565 actively managed funds; the sample period covers all horizons under data availability from the start of the CSMAR Chinese mutual fund database. For the US sample, it includes 2,412 actively-managed funds from 2004 to 2016.

Table 5-1 Summary Statistics for Cash Holdings and Fund Characteristics of the China and US Mutual Funds

This table reports summary statistics for cash holdings, equity holdings, abnormal cash holdings, risk-adjusted alphas, betas, active investment factors and fundamental fund characteristics of the China and US mutual fund markets. Independent variables include risk-adjusted alphas and risk betas calculated from the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5), the Q-factor model (QF) from Hou, Xue and Zhang (2014) and the mispricing-factor model (MF) from Stambaugh and Yuan (2016) with 24-month rolling window regressions. Active investment factors include fund diversification, industry concentration index, reliance on public information, active share, fund-report attention and return gap. Fundamental fund characteristics include fund size and fund family size (in millions), log of fund size, log of fund family size, fund age, total expense ratio, lagged fund flow and prior 12-month return volatility. Panel A reports summary statistics and Panel B reports Pearson correlation matrix.

Panel A: China Funds

Variables	**N**	**Mean**	**SD**	**Min**	**P25**	**Median**	**P75**	**Max**
Asset allocations								
Abnormal cash	12907	0.004	0.69	-9.64	-0.06	-0.01	0.06	10.35
Equity holdings	12887	0.76	0.15	0.00	0.70	0.79	0.87	0.96
Cash holdings	12896	0.12	0.09	0.00	0.06	0.09	0.15	0.98
Fundamental characteristics								
Fund return	12704	0.01	0.10	-0.81	-0.05	0.01	0.05	0.98
Fund size	12896	2913.83	3839.42	2.80	392.96	1450.60	3854.36	32566.45
Fund size (log)	12896	20.89	1.54	14.85	19.79	21.10	22.07	24.21

Table 5-1 (continued)

Lagged flow	12147	-0.04	0.29	-0.63	-0.12	-0.04	-0.01	2.93
Total expense ratio	12768	0.05	0.02	0.00	0.05	0.06	0.06	0.09
Return volatility	12666	0.07	0.03	0.01	0.05	0.06	0.08	0.19
Flow volatility	11866	0.16	0.22	0.00	0.03	0.09	0.19	2.48
Age (quarter)	12907	16.32	11.63	0.00	7.00	14.00	24.00	57.00
Age (quarter) log	12907	2.44	0.96	0.00	1.95	2.64	3.18	4.04
Family size	12896	1932.16	1496.58	8.63	790.18	1536.28	2755.20	8663.64
Family size (log)	12896	21.02	0.98	15.97	20.49	21.15	21.74	22.88
Risk-adjusted alphas								
CAPM alpha	11912	0.22%	0.87%	-3.71%	-0.25%	0.20%	0.67%	7.09%
FF3 alpha	11912	-0.05%	1.04%	-5.83%	-0.59%	-0.04%	0.48%	11.67%
FF4 alpha	11912	0.11%	1.04%	-7.17%	-0.39%	0.08%	0.56%	12.28%
FF5 alpha	11912	0.00%	1.08%	-6.21%	-0.56%	0.01%	0.56%	11.78%
QF alpha	11912	-0.78%	1.37%	-9.17%	-1.53%	-0.67%	0.01%	9.83%
Risk betas								
Beta MKT CAPM	11912	0.76	0.21	-0.23	0.65	0.77	0.88	1.76
Beta MKT FF3	11912	0.71	0.21	-0.53	0.60	0.73	0.84	2.19
Beta SMB FF3	11912	0.12	0.34	-1.91	-0.09	0.07	0.30	1.51
Beta HML FF3	11912	-0.14	0.44	-2.66	-0.38	-0.14	0.08	2.08
Beta MKT FF4	11912	0.77	0.22	-0.96	0.66	0.77	0.89	2.21
Beta SMB FF4	11912	0.06	0.32	-2.23	-0.11	0.05	0.23	1.74
Beta HML FF4	11912	-0.19	0.43	-4.42	-0.39	-0.16	0.04	2.25
Beta UMD FF4	11912	0.29	0.33	-2.11	0.09	0.29	0.49	2.19
Beta MKT FF5	11912	0.76	0.24	-0.92	0.65	0.77	0.90	2.28
Beta SMB FF5	11912	0.21	0.44	-2.39	-0.05	0.17	0.45	2.29
Beta HML FF5	11912	-0.15	0.46	-4.32	-0.39	-0.16	0.07	2.87
Beta CMA FF5	11912	-0.21	0.71	-4.07	-0.53	-0.12	0.17	4.07
Beta RMW FF5	11912	0.22	0.67	-3.76	-0.10	0.22	0.59	4.31
Beta MKT QF	11912	0.79	0.21	-0.61	0.68	0.80	0.91	2.51
Beta SMB QF	11912	0.32	0.41	-2.17	0.06	0.29	0.56	1.88
Beta I/A QF	11912	-0.21	0.43	-3.07	-0.45	-0.14	0.00	2.29
Beta ROE QF	11912	0.29	0.42	-2.56	0.05	0.28	0.50	3.47
Active investment measures								
Diversification	12381	3.90	0.60	0.00	3.53	3.85	4.23	6.85
Industry concentration index	8786	0.04	0.04	0.00	0.02	0.04	0.05	0.58
Reliance on public information	7818	0.16	0.24	-0.15	0.01	0.07	0.24	0.97
Active share	8527	0.12	0.09	0.00	0.05	0.10	0.18	0.56
Fund-report attention	12619	3.54	0.62	-4.77	3.23	3.68	3.96	4.54
Return gap	8401	-0.09	0.15	-0.71	-0.16	-0.06	0.01	0.25

US Funds

Variables	**N**	**Mean**	**SD**	**Min**	**P25**	**Median**	**P75**	**Max**
Asset allocations								
Abnormal cash	89628	0.03	0.04	-0.01	0.01	0.02	0.04	0.25
Equity holdings	70585	0.24	0.40	0.00	0.01	0.03	0.14	8.94
Cash holdings	101862	0.00	0.03	-0.22	-0.03	-0.01	0.01	0.35

Table 5-1 (continued)

Fundamental characteristics							
Fund Return	104272	0.02	0.09	-0.60	-0.02	0.03	0.08	0.88
Fund size	104272	1576.27	5622.26	20.00	101.94	332.72	1111.67	187310.43
Fund size (log)	104272	19.71	1.62	16.81	18.44	19.62	20.83	25.96
Lagged flow	103003	0.02	0.16	-0.31	-0.04	-0.01	0.03	2.01
Expense ratio	101817	0.01	0.00	0.00	0.01	0.01	0.01	0.06
Return volatility	102107	0.04	0.02	0.01	0.03	0.04	0.05	0.12
Flow volatility	102040	0.12	0.37	0.00	0.02	0.04	0.09	6.04
Turnover	96610	0.73	0.59	0.02	0.31	0.57	0.96	4.34
Age (quarter)	104272	57.13	51.00	0.00	25.00	45.00	71.00	369.00
Family size	104272	52921.85	124746.97	20.01	2072.77	13817.89	40133.33	834090.24
Family size (log)	104272	22.87	2.29	16.81	21.45	23.35	24.42	27.45
Manager tenure	85911	11.06	7.23	0.08	5.67	9.92	15.00	81.83
Manager tenure (log)	85911	2.13	0.88	-2.53	1.74	2.29	2.71	4.40
MS 3-year rating	93531	3.10	1.12	1.00	2.00	3.00	4.00	5.00
MS overall rating	93531	3.19	1.02	1.00	3.00	3.00	4.00	5.00
Risk-adjusted alphas								
CAPM alpha	102761	-0.004%	0.444%	-1.665%	-0.263%	-0.037%	0.212%	1.859%
FF3 alpha	103458	-0.048%	0.373%	-1.698%	-0.246%	-0.056%	0.142%	1.649%
FF4 alpha	103505	-0.051%	0.362%	-1.644%	-0.245%	-0.059%	0.135%	1.619%
FF5 alpha	103532	-0.046%	0.399%	-1.895%	-0.255%	-0.056%	0.150%	1.929%
QF alpha	103185	-0.048%	0.433%	-1.801%	-0.285%	-0.052%	0.177%	1.702%
MF alpha	103967	-0.043%	0.413%	-2.570%	-0.253%	-0.053%	0.152%	2.570%
Risk betas								
Beta MKT CAPM	103395	1.05	0.22	0.21	0.93	1.03	1.16	1.86
Beta MKT FF3	103905	1.00	0.16	0.22	0.92	1.00	1.08	1.82
Beta SMB FF3	103759	0.24	0.38	-0.80	-0.07	0.15	0.55	1.32
Beta HML FF3	103999	0.01	0.32	-1.22	-0.19	0.02	0.21	1.30
Beta MKT FF4	103892	1.00	0.16	0.16	0.92	1.00	1.08	1.82
Beta SMB FF4	103763	0.23	0.37	-0.87	-0.07	0.14	0.52	1.31
Beta HML FF4	103992	0.00	0.31	-1.25	-0.19	0.01	0.20	1.22
Beta UMD FF4	104039	0.02	0.16	-0.80	-0.07	0.01	0.09	0.89
Beta MKT FF5	103882	0.99	0.16	0.12	0.91	1.00	1.07	1.88
Beta SMB FF5	103818	0.24	0.38	-0.92	-0.07	0.14	0.55	1.37
Beta HML FF5	103985	0.01	0.31	-1.43	-0.19	0.01	0.20	1.68
Beta CMA FF5	104011	-0.10	0.38	-2.30	-0.31	-0.08	0.11	1.92
Beta RMW FF5	104040	-0.01	0.29	-1.79	-0.16	0.00	0.15	1.37
Beta MKT QF	103853	0.99	0.15	0.14	0.91	0.99	1.07	1.69
Beta SMB QF	103710	0.23	0.37	-0.98	-0.06	0.14	0.51	1.25
Beta I/A QF	103909	-0.08	0.33	-1.62	-0.26	-0.05	0.13	1.04
Beta ROE QF	103955	0.01	0.26	-1.57	-0.12	0.03	0.16	1.03
Beta MKT MF	103888	0.98	0.16	0.08	0.90	0.99	1.06	1.76
Beta SIZE MF	103836	0.22	0.38	-1.04	-0.08	0.13	0.51	1.43
Beta MGMT MF	104128	-0.11	0.31	-1.74	-0.29	-0.09	0.07	1.10
Beta PERF MF	104008	0.00	0.16	-0.86	-0.09	0.01	0.10	0.74

Table 5-1 (continued)

Panel B: China Funds

Correlation	Abnormal cash	Fund return	Fund size	Lagged flow	Total expense ratio	Volatility	Age (quarter)	Family size	Flow volatility	CAPM alpha	Beta MKT CAPM
Abnormal cash	1.00	-0.06	0.06	0.03	0.00	0.00	-0.01	0.05	0.07	0.00	0.03
Fund return	-0.06	1.00	-0.05	0.04	0.01	-0.09	-0.02	-0.03	0.00	0.19	-0.10
Fund size	0.06	-0.05	1.00	0.03	-0.14	0.09	0.15	0.54	-0.14	0.09	0.05
Lagged flow	0.03	0.04	0.03	1.00	0.00	0.07	-0.06	0.04	0.38	0.13	0.06
Total expense ratio	0.00	0.01	-0.14	0.00	1.00	0.07	-0.18	-0.06	0.08	-0.02	-0.01
Volatility	0.00	-0.09	0.09	0.07	0.07	1.00	0.00	0.03	0.31	-0.12	0.56
Age (quarter)	-0.01	-0.02	0.15	-0.06	-0.18	0.00	1.00	0.09	-0.22	-0.18	0.18
Family size	0.05	-0.03	0.54	0.04	-0.06	0.03	0.09	1.00	-0.06	0.10	0.00
Flow volatility	0.07	0.00	-0.14	0.38	0.08	0.31	-0.22	-0.06	1.00	0.13	0.10
CAPM alpha	0.00	0.19	0.09	0.13	-0.02	-0.12	-0.18	0.10	0.13	1.00	-0.26
Beta MKT CAPM	0.03	-0.10	0.05	0.06	-0.01	0.56	0.18	0.00	0.10	-0.26	1.00

Table 5-1 (continued)

US Funds

Correlation	Abnormal cash	Fund return	Fund size	Lagged flow	Expense ratio	Return volatility	Flow volatility	Turnover	Age (quarter)	Family size	Manager tenure	CAPM alpha	Beta MKT CAPM
Abnormal cash	1.00	0.03	0.04	0.04	-0.01	-0.02	-0.03	-0.06	0.05	0.02	0.08	0.02	-0.01
Fund return	0.03	1.00	0.01	0.06	0.02	0.01	0.00	-0.03	0.00	0.02	0.00	0.07	0.00
Fund size	0.04	0.01	1.00	-0.04	-0.19	-0.06	-0.06	-0.11	0.28	0.39	0.15	0.02	-0.05
Lagged Flow	0.04	0.06	-0.04	1.00	0.07	-0.03	0.25	-0.01	-0.17	-0.01	-0.02	0.23	-0.06
Expense ratio	-0.01	0.02	-0.19	0.07	1.00	0.12	0.09	0.12	-0.14	-0.28	0.02	0.00	0.09
Return volatility	-0.02	0.01	-0.06	-0.03	0.12	1.00	0.01	0.16	-0.05	-0.06	0.00	0.14	0.31
Flow volatility	-0.03	0.00	-0.06	0.25	0.09	0.01	1.00	0.05	-0.15	-0.04	-0.05	0.06	-0.01
Turnover	-0.06	-0.03	-0.11	-0.01	0.12	0.16	0.05	1.00	-0.08	0.01	-0.16	-0.03	0.15
Age (quarter)	0.05	0.00	0.28	-0.17	-0.14	-0.05	-0.15	-0.08	1.00	0.12	0.18	-0.08	-0.05
Family size	0.02	0.02	0.39	-0.01	-0.28	-0.06	-0.04	0.01	0.12	1.00	-0.09	0.00	0.01
CAPM alpha	0.02	0.07	0.02	0.23	0.00	0.14	0.06	-0.03	-0.08	0.00	0.07	1.00	-0.21
Beta MKT CAPM	-0.01	0.00	-0.05	-0.06	0.09	0.31	-0.01	0.15	-0.05	0.01	-0.04	-0.21	1.00

Figure 5-1 Aggregate Cash Holdings in China and the CSI300 Index

The figure shows the mean and median of aggregate cash holdings calculated as average cash holdings across all sample funds in China and the CSI300 index from 2005Q2 to 2015Q4.

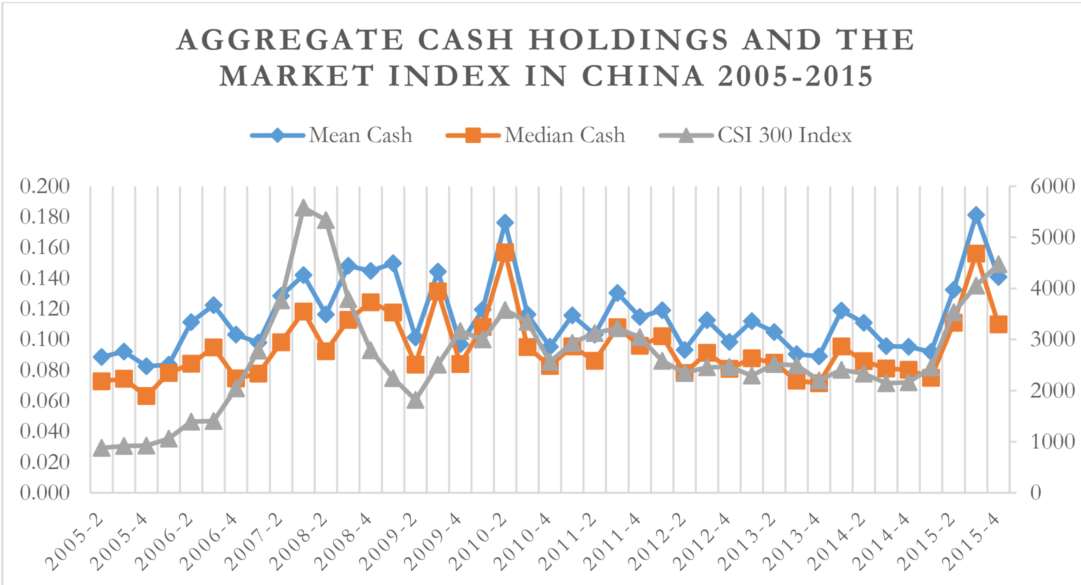
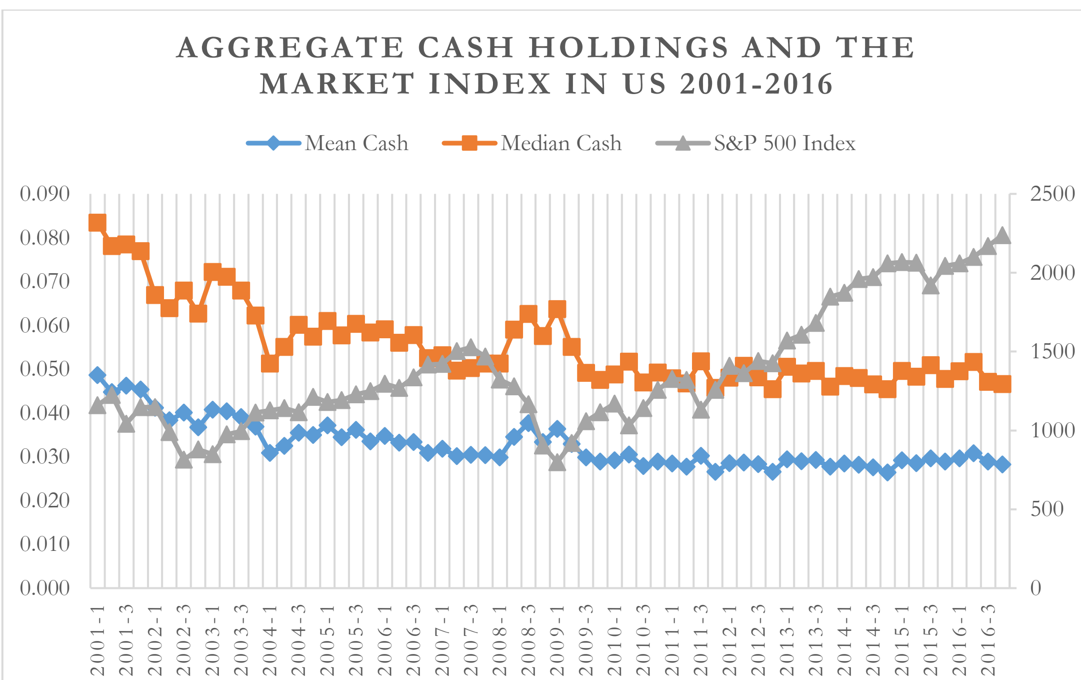


Figure 5-2 Aggregate Cash Holdings in the US and the SPX500 Index

The figure shows the mean and median of aggregate cash holdings calculated as average cash holdings across all sample funds in the US and the SPX500 index from 2001Q1 to 2016Q4.



I present summary statistics for fundamental fund characteristics, risk betas, risk-adjusted alphas and active measures of my sample in Table 5-1. In China, average cash holdings are about 12% across all funds in the sample. From Figure 5-1, the aggregate mean of cash holdings rises from 9.81% in 2007Q1 to 14.42% in 2009Q3. Similarly, it rises from 9.19% in 2015Q1 to 18.12% in 2015Q3. In the US, average cash holdings are less than 2%. From Figure 5-2, the US aggregate mean of cash holdings increases from 2.98% in 2008Q1 to 3.64% 2009Q1 and it remains at a low level of about 2.94% after 2013Q1. This indicates that fund managers tend to hold more cash when the market is volatile, especially during a financial crisis.

5.5 What Determines Fund Cash Holdings?

To explore the determinants of fund cash holdings, I regress cash holdings on equity holdings, risk betas from the Fama-French-Carhart model and fundamental fund characteristics. I also control for active measures using portfolio holding data in China.[27] I run double-clustered regressions to get coefficients and control for both fund and time effects following Petersen (2009) and Thompson (2011).

$$Cash\ holdings_{i,t} = \alpha_0 + \beta_i^{equity\ holdings} * equity\ holdings_{i,t-1} + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \varepsilon_{i,t}$$

(Eq. 5-1)

[27] Due to the availability of fund holdings data, I exclude active investment factors in the cash determinant regression of the US market.

Table 5-2 Determinants of Cash Holdings

This table shows the determinants of cash holdings. The dependent variable is quarterly cash holdings. Independent variables include quarterly equity holdings, fund returns and risk betas calculated from the Fama-French-Carhart model (FF4) with 24-month rolling window regressions. Active investment factors include fund diversification, industry concentration index, reliance on public information, active share, fund-report attention and return gap. Fundamental fund characteristics include fund return, log of fund size, log of fund family size, fund age, total expense ratio, lagged fund flow, prior 12-month return volatility and prior 12-month flow volatility.

$$Cash\ holdings_{i,t} = \alpha_0 + \beta_i^{equity\ holdings} * equity\ holdings_{i,t-1} + \sum \beta_i^{fundamental} * fundamentals_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \varepsilon_{i,t}$$

(5-1)

I run double-clustered regressions to get the coefficients. Decomposed R-squareds (individual R^2 %) calculated with Shapley-own Methods are listed for each regression. Regarding the regression, cluster effects are studied with their standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at 1%, 5% and 10% levels respectively.

Panel A: China Funds

	(1)		(2)		(3)		(4)	
Variables	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**	**Coeff.**	**Ind. R^2**
Equity Holdings	-0.068***	9.14	-0.076***	10.20	-0.066***	8.68	-0.061***	8.03
	(-4.140)		(-4.954)		(-3.128)		(-3.068)	
Fund size (log)	-0.010***	29.93	-0.009***	27.49	-0.007***	14.36	-0.006***	14.39
	(-5.258)		(-5.171)		(-2.882)		(-2.766)	
Family size log	0.004*	3.33	0.003	3.26	-0.001	3.68	-0.001	3.79
	(1.668)		(1.551)		(-0.166)		(-0.274)	
Age (quarter) log	-0.010***	12.85	-0.011***	13.60	-0.015***	14.42	-0.016***	14.62
	(-3.067)		(-3.450)		(-3.529)		(-3.724)	
Total expense ratio	0.180*	3.95	0.198**	3.98	0.170	3.67	0.167	3.42
	(1.799)		(1.961)		(1.276)		(1.255)	
Lagged flow	-0.013**	1.46	-0.014**	1.44	-0.011**	0.89	-0.009	0.77
	(-2.376)		(-2.450)		(-2.084)		(-1.547)	
Return volatility	0.483***	31.06	0.437***	25.55	0.465***	22.16	0.442***	19.66
	(4.941)		(4.524)		(4.939)		(4.038)	
Flow volatility	0.016	8.29	0.018*	8.24	0.012	5.35	0.012	5.10
	(1.532)		(1.681)		(0.828)		(0.792)	

Table 5-2 (continued)

Fundamental subtotal R^2		**100.00**		**93.77**		**73.21**		**69.77**
Diversification					-0.000	1.89	-0.001	2.22
					(-0.111)		(-0.339)	
Industry concentration index					-0.100	1.00	-0.098	1.05
					(-1.433)		(-1.428)	
Reliance on public information					0.005	3.08	0.004	2.81
					(0.749)		(0.692)	
Fund-report attention					-0.017**	16.33	-0.017**	15.56
					(-2.161)		(-2.029)	
Active share					-0.053**	4.18	-0.060**	4.18
					(-2.042)		(-2.342)	
Return gap					0.002	0.31	-0.001	0.42
					(0.147)		(-0.046)	
Active subtotal R^2						**26.79**		**26.24**
Fund return			-0.021	1.45			-0.023	0.78
			(-0.385)				(-0.450)	
Beta MKT FF4			0.019	1.75			0.006	0.60
			(1.278)				(0.387)	
Beta SMB FF4			0.002	1.21			-0.007	0.25
			(0.337)				(-0.656)	
Beta HML FF4			-0.001	0.53			0.002	0.20
			(-0.100)				(0.219)	
Beta UMD FF4			-0.005	1.30			-0.010*	2.16
			(-1.098)				(-1.699)	
Risk subtotal R^2				**4.79**				**3.20**
Intercept	0.273***		0.265***		0.385***		0.391***	
	(5.484)		(5.287)		(5.067)		(5.025)	
Cluster quarter effects	Yes		Yes		Yes		Yes	
Cluster fund effects	Yes		Yes		Yes		Yes	
Observations	11,419		10,980		4,885		4,698	
R-squared	0.0938		0.0985		0.1236		0.1274	
Adj. R-squared	0.0931		0.0974		0.121		0.124	

Table 5-2 (continued)

Panel B: US Funds

	(1)		(2)		(3)		(4)	
Variables	**Coeff.**	**Ind. R2**	**Coeff.**	**Ind. R2**	**Coeff.**	**Ind. R2**	**Coeff.**	**Ind. R2**
Equity Holdings	0.003**	4.59	0.003**	3.56	0.003***	3.08	0.002**	1.42
	(2.379)		(2.329)		(2.642)		(2.135)	
Fund size (log)	0.002***	6.26	0.003***	9.26			0.003***	4.43
	(3.553)		(5.538)				(5.841)	
Family size log	-0.003***	52.25	-0.002***	34.50			-0.002***	14.21
	(-7.703)		(-6.812)				(-6.413)	
Lagged flow	0.024***	36.90	0.024***	25.97			0.022***	11.29
	(12.297)		(11.595)				(11.341)	
Age			-0.002***	4.44			-0.002**	1.68
			(-2.984)				(-2.486)	
Total expense ratio			0.789***	20.94			0.746***	9.43
			(5.285)				(5.262)	
Return volatility			-0.035*	0.90			0.073***	1.00
			(-1.660)				(3.239)	
Flow volatility			-0.002**	0.43			-0.001	0.18
			(-1.992)				(-1.352)	
Fundamental subtotal R^2		**100.00**		**100.00**		**3.08**		**43.63**
Fund return					-0.009	0.60	-0.011*	0.45
					(-1.256)		(-1.801)	
Beta MKT FF4					-0.044***	70.36	-0.047***	43.08
					(-8.970)		(-10.039)	
Beta SMB FF4					0.008***	15.32	0.006***	7.37
					(5.858)		(4.208)	
Beta HML FF4					0.005**	9.30	0.004**	4.60
					(2.255)		(2.002)	
Beta UMD FF4					-0.002	1.34	-0.002	0.86
					(-0.705)		(-0.470)	
Risk subtotal R^2						**96.31**		**55.92**

Table 5-2 (continued)

Intercept	0.057***	0.031***	0.072***	0.065***
	(6.989)	(2.964)	(14.403)	(6.263)
cluster quarter effects	Yes	Yes	Yes	Yes
cluster fund effects	Yes	Yes	Yes	Yes
Observations	65,193	62,506	65,303	62,157
R-squared	0.0323	0.0407	0.0499	0.0849
Adj. R-squared	0.0322	0.0406	0.0498	0.0847

Table 5-2 shows the results of four regression specifications and decomposed R-squared is also calculated for each independent variable.

For the China funds in Table 5-2 Panel A, in specification 1, I only include fundamental fund characteristics in the regression. It shows that small and young funds with higher past volatility and less lagged flow tend to hold more cash. Size (29.93%), return volatility (31.06%) and fund age (12.85%) are the top three determinants, which have large explanatory power for cash holdings. In specification 2, fund performance and risk loadings on market, size, value and momentum risk factors are also included in the regression. It shows that the performance-level variable and risk loadings are not significantly related to cash holdings. In specification 3, active investment factors like fund diversification, industry concentration index, reliance on public information, fund-report attention, active shares and return gap are included in the regression. Funds with greater report attention and higher active share tend to maintain less cash.

More specifically, in specification 4, I include all the variables from fundamental fund characteristics, performance, risk loadings and active measures in the regression.

Within the fundamental characteristics, first, a higher equity holding indicates a lower cash level. The coefficient of equity holding is -0.061 (t=-3.068, R^2=8.063%), which is significant at the 1% level. Second, consistent with Chen et al. (2004), small funds hold more cash, which is in line with the idea that funds can maintain better liquidity with more capital. Fund size shows a significant coefficient of -0.006 (t=-2.766, R^2= 14.39%) at the 1% level. Third, young funds tend to hold more cash. The log of fund age is negatively related to cash holding (-0.016, t=-3.724, R^2=14.62%). It is significant at the 1% level. Fourth, return volatility has a positive effect on cash. Return volatility has a coefficient of 0.442 (t=4.038, R^2=19.66%), which is significant at the 1% level. Larger volatility of returns might induce potential redemptions, so fund managers hold more cash to cover it.

Within the risk beta group, it shows little evidence that fund managers determine their holdings based on common risk factors. R-squared of the risk beta group is 3.20%. It shows that fund managers rely more on fundamental fund characteristics (69.77%) and active investment factors (26.24%) to determine their cash levels.

Within the active investment group, fund-report attention is significantly and negatively associated with cash holding (-0.017, t=2.029, R^2= 15.56%) at the 5% level. On the one hand, greater public attention of fund holdings can reduce the search costs of fund investors (Sirri and Tufano, 1998). This indirectly provides fund managers with more capital to maintain liquidity which motivates them to hold cash at a low level. On the other hand, it might imply that mutual fund managers hold more cash to accommodate fund outflows when their portfolios are covered less by analysts. In addition, active share also shows a significant negative coefficient (-0.06, t=-2.342) at the 5% level, with a relatively lower R-squared of 4.18%. It shows that more active strategies may lead to lower cash holdings in funds. As active shares predict better performance (Cremers and Petajisto, 2009), a large deviation of a stock holding from its benchmark will require more capital to invest, which reduces cash.

Overall, consistent with Hypothesis One, the results imply that, first, fund managers in China show relatively fewer concerns over risk beta in maintaining their cash holdings. For risk factors, the risk beta group shows the lowest decomposed R-squared (3.2%), with little significance to determine fund cash holdings. For non-risk factors, the fundamental characteristics group accounts for 69.77% and the active investment group for 26.24% of cash holdings. Second, for fundamental fund characteristics, return volatility is positively related to cash holdings, while fund equity holding, fund size and fund age have a negative effect on it. Third, for active investment factor, active share and fund-report attention are negatively associated with cash holdings.

For the US funds in Table 5-2 Panel B, in specification 1, I include the main fundamental characteristic in the regression. It shows that funds with higher equity holding, larger size, smaller fund family size and higher lagged flows tend to hold more cash. In specification 2, alternative fund characteristics are included. Funds of young age with higher fees and lower flow volatility maintain their cash at a higher level. In specification 3, I include risk betas with equity holding and fund returns. It shows that market risk beta (MKT) negatively affects cash holdings with a coefficient of -0.044 (t=-8.97) that is significant at 1% level. Market risk beta also has the highest explanatory power of 70.36%. Size risk beta (SMB) has a significant coefficient of 0.008 (t=5.828) at the 1% level, with an R-squared of 15.32%. Value risk beta (HML) has a significant coefficient of 0.005 (t=2.255) at the 5% level, with an R-squared of 9.3%.

More specifically, in specification 4, I include all the variables in the regression. Within the fundamental fund characteristics group, first, equity holdings positively predict cash holdings, with a coefficient of 0.002 (t=2.135, R^2=1.42%) that is significant at the 5% level. It suggests that US fund managers with higher equity holdings tend to hold more cash. This might be attributed to the concerns of fund managers over covering alternative costs in transactions. Second, fund size has a positive coefficient of 0.003 (t=5.841, R^2=4.43%), which is significant at the 1% level. As large funds suffer from the scale-decreasing returns (Chen et al., 2004), fund managers might keep more cash and patiently target better investment ideas. Third, fund family size shows a negative coefficient of -0.002 (t=6.413, R^2=14.21%) for fund cash holdings. The coefficient of fund family size is significant at the 1% level. It might indicate that large fund families are more aggressive and hold less cash in their funds, which is consistent with Bhojraj, Cho and Yehuda (2011), as large fund families tend to outperform their lower fund family size peers. Also, funds in larger families may tend to retain less cash to create different strategies, so as to generate star funds (Nanda, Wang and Zheng, 2004). Fourth, lagged fund flow has a positive coefficient of 0.022 (t=11.341) that is significant at the 1% level, with R-squared at 11.29%. One the one hand, it suggests that skilled fund managers hold more cash to reduce the price impact on their portfolios (Chordia, 1996; Lou, 2012). On the other hand, it implies that fund managers might trade infrequently when they have money inflows. They are more patient, waiting for alternative investment opportunities or the right market timing (Yan, 2006). Fifth, fund age has a negative coefficient -0.002 (t=-2.486, R^2= 1.68%) for cash holding. The coefficient of fund age is significant at the 5% level. It indicates that young funds tend to hold more cash. Young funds face more competition as active skills develop over time (Pástor, Stambaugh and Taylor (2015), which might motivate young funds to hold more cash. Sixth, total expense ratio is positively associated with cash holdings with a decomposed R-squared of 9.43%. It has the largest coefficient of 0.746 (t=5.262) among cash determinants in Column 4. The coefficient of total expense is significant at the 1% level. This is consistent with Yan (2006) as skilled fund managers with higher fees tend to trade more patiently and to keep more cash, so higher fees might indicate superior skills (Sheng, Simutin and Zhang, 2017). Finally, return volatility also positively predicts cash holding with a coefficient of 0.073 (t=3.239, R^2=1%) that is significant at the 1% level. It shows that fund managers hold more cash to cover redemptions or other costs when they are volatile in performance (Chordia, 1996; Chernenko and Sunderam 2016).

Within the risk beta group, market beta (MKT) shows a negative and significant coefficient of -0.047 (t=-10.039) at the 1% level on cash holdings which account for the largest R-squared of 43.08% in the risk beta group. It indicates that US fund managers might be largely concerned with the systematic risk taken in their portfolios to decide their cash levels, and they might utilize higher beta stock as implicit leverage in their investments (Boguth and Simutin, 2018). While the coefficient of size risk beta (SMB) is 0.006 (t=4.208) that is significant at the 1% level. The coefficient of value risk beta (HML) is 0.004 (t=2.002) that is significant at the 5% level. This suggests that fund managers adjust their cash holdings and hold more cash to cover the risk from common risk factors (Karceski, 2002; Christoffersen and Simutin, 2017). Size risk beta shows explanatory power of 7.37% and for value risk beta it is 4.60%, which are relatively lower than the explanatory power of market risk beta. It implies that market risk is the main concern of US fund managers.

In sum, the results show that, first, consistent with my Hypothesis One, the US funds show more concerns over the risk factors in their cash allocations. The risk beta group accounts for the largest R-squared of cash holdings at 55.92%, while fundamental characteristics have an R-squared of 43.63%. Among the risk beta group, market risk beta outperforms size risk and value risk betas in explanatory power for cash. This is consistent with the beta anomaly that investing in lower market beta stocks offer more significant returns than higher beta stocks (Frazzini and Pedersen, 2014). In addition, it supports that market beta can measure the tightness of leverage constraints (Boguth and Simutin, 2018). Funds might keep more cash to keep their portfolios at lower market risk levels. Second, equity holding, fund size, lagged flow, total expense ratio and return volatility positively predict cash holdings, while fund family size and fund age show negatively effect on it.

5.6 How do Abnormal Cash Holdings Relate to Investment Strategies?

To understand the investment strategies of fund managers skilled in cash management, I explore the role of abnormal cash holdings in their future risk incentive, which is measured by risk beta. I apply the Fama-Macbeth (1973) regressions to obtain residuals as abnormal cash holdings based on Equation 5-1 following Simutin (2013).

$$Fund\ Beta_{i,t} = \alpha_0 + \beta_1 * abnormal\ cash_{i,t-1} + \beta_2 * fund\ size_{i,t-1} + \beta_3 * family\ size_{i,t-1} + \beta_4 * age_{i,t-1} + \beta_5 * expense_{i,t-1} + \beta_6 * flows_{i,t-1} + \beta_7 * return\ volatility_{i,t-1} + \beta_8 * flow\ volatility_{i,t-1} + \beta_9 * fund\ returns_{i,t-1} + \varepsilon_{i,t}$$

(Eq. 5-2)

Table 5-3 ACH and Funds' Investment Strategies

This table reports the results for how funds with abnormal cash tilt their portfolios towards different risk betas. Dependent variables are risk betas calculated from the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model, the Fama-French five-factor model, the Q-factor model and the mispricing-factor model with 24-month rolling window regressions. The main dependent variable is quarterly abnormal cash holding (ACH). Controls variables include log of fund size, log of fund family size, fund age, total expense ratio, lagged fund flow, prior 12-month return volatility and prior 12-month flow volatility.

$$Fund\ Beta_{i,t} = \alpha_0 + \beta_1 * abnormal\ cash\ holdings_{i,t-1} + \beta_2 * fund\ size_{i,t-1} + \beta_3 * family\ size_{i,t-1} + \beta_4 * age_{i,t-1} + \beta_5 * expense_{i,t-1} + \beta_6 * flows_{i,t-1} + \beta_7 * return\ volatility_{i,t-1} + \beta_8 * flow\ volatility_{i,t-1} + \beta_9 * fund\ returns_{i,t-1} + \varepsilon_{i,t} \quad (5\text{-}2)$$

I run double-clustered regressions to get the coefficients. Regarding the regressions, cluster effects are studied with their standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at 1%, 5% and 10% levels respectively.

Panel A: China Funds

Variables	(1) MKT beta	(2) SMB beta	(3) HML beta	(4) UMD beta	(5) RMW beta	(6) CMA beta	(7) I/A beta	(8) ROE beta
ACH	0.007	-0.007	-0.023	0.023	0.015	0.026	0.052*	0.044**
	(0.989)	(-0.129)	(-0.731)	(1.283)	(0.582)	(1.092)	(1.805)	(2.182)
Fund size (log)	-0.016***	-0.007	0.004	-0.006	0.008	0.078***	0.030***	0.003
	(-3.349)	(-0.901)	(0.401)	(-0.599)	(0.425)	(3.879)	(3.192)	(0.324)
Family size (log)	0.007	-0.022**	-0.039***	-0.018*	-0.009	0.001	0.006	-0.012
	(1.141)	(-2.143)	(-3.101)	(-1.721)	(-0.479)	(0.047)	(0.418)	(-1.115)
Age (log)	0.044***	-0.040**	-0.062***	0.024*	-0.054*	-0.179***	-0.034	-0.004
	(3.731)	(-2.391)	(-3.193)	(1.677)	(-1.772)	(-4.453)	(-1.282)	(-0.157)
Total expense ratio	0.049	1.011**	-0.715	-0.368	0.024	-0.212	-0.956*	-0.891
	(0.163)	(2.566)	(-1.472)	(-0.632)	(0.025)	(-0.240)	(-1.704)	(-1.445)
Lagged flow	0.021**	0.076**	0.096**	0.002	0.043	0.034	-0.026	-0.056
	(2.037)	(2.167)	(2.348)	(0.078)	(0.782)	(0.443)	(-0.697)	(-1.266)
Volatility	3.038***	0.264	-2.585***	-1.445***	2.772**	2.454*	-0.394	-0.330
	(9.905)	(0.602)	(-2.869)	(-3.060)	(2.067)	(1.938)	(-0.486)	(-0.511)
Flow volatility	-0.053*	-0.014	-0.109**	0.081	-0.218**	-0.117	0.083	0.070
	(-1.810)	(-0.374)	(-2.492)	(1.553)	(-2.189)	(-1.141)	(1.152)	(0.922)
Fund return	0.136	0.248	0.023	-0.339	0.140	0.224	-0.424	-0.506
	(0.650)	(1.611)	(0.073)	(-1.598)	(0.320)	(0.433)	(-1.135)	(-1.544)
Intercept	0.640***	0.707***	0.944***	0.852***	0.239	-1.549***	-0.813***	0.557**
	(4.790)	(3.552)	(3.464)	(3.977)	(0.538)	(-3.310)	(-2.692)	(2.305)

Table 5-3 (continued)

Cluster quarter effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,449	10,449	10,449	10,449	10,449	10,449	10,449	10,449
R-squared	0.275	0.0376	0.0671	0.0329	0.0194	0.0630	0.0346	0.0190
Adjusted R-squared	0.275	0.0367	0.0663	0.0321	0.0185	0.0622	0.0338	0.0181

Panel B: US Funds

Variables	(1) MKT beta	(2) SMB beta	(3) HML beta	(4) UMD beta	(5) RMW beta	(6) CMA beta	(7) I/A beta	(8) ROE beta	(9) MGMT beta	(10) PERF beta
ACH	-0.175**	0.192*	-0.100	-0.156***	-0.090	-0.106	0.045	-0.133*	-0.207**	-0.120**
	(-2.426)	(1.710)	(-1.047)	(-3.374)	(-1.295)	(-0.959)	(0.476)	(-1.781)	(-2.454)	(-2.297)
Fund size (log)	-0.001	-0.010*	0.002	-0.006***	-0.008***	0.002	0.005	-0.010***	-0.002	-0.007***
	(-0.569)	(-1.918)	(0.531)	(-3.743)	(-3.460)	(0.577)	(1.180)	(-3.952)	(-0.621)	(-3.599)
Family size (log)	0.013***	0.016***	-0.010***	0.005***	-0.005***	-0.007***	-0.013***	-0.002	-0.013***	0.003**
	(8.347)	(4.434)	(-3.459)	(4.725)	(-3.041)	(-2.838)	(-4.841)	(-1.259)	(-5.303)	(2.424)
Age (log)	-0.007	-0.026***	-0.034***	-0.003	-0.003	-0.023***	-0.025***	0.007	-0.009	0.014***
	(-1.423)	(-3.114)	(-5.464)	(-0.996)	(-0.837)	(-3.530)	(-4.110)	(1.595)	(-1.434)	(4.536)
Total expense ratio	6.463***	19.662***	-3.455**	1.275**	-5.958***	-7.027***	-8.904***	-3.299***	-10.225***	-0.847
	(6.192)	(11.119)	(-2.533)	(2.006)	(-7.145)	(-5.303)	(-6.897)	(-3.502)	(-8.477)	(-1.269)
Lagged flow	-0.074***	-0.023	0.099***	0.032**	0.049***	0.036	0.041	0.071***	0.066**	0.001
	(-3.724)	(-1.149)	(3.371)	(2.333)	(3.146)	(1.208)	(1.291)	(4.160)	(2.243)	(0.040)
Return volatility	3.355***	4.869***	-1.562***	-0.752***	-0.975*	-1.204	-1.443***	0.123	-1.829***	-0.371
	(5.590)	(5.740)	(-4.496)	(-3.196)	(-1.807)	(-1.644)	(-3.160)	(0.205)	(-4.732)	(-1.636)
Flow volatility	-0.008	-0.038***	-0.010	-0.006*	-0.002	-0.007	-0.000	0.001	0.006	0.002
	(-1.636)	(-5.468)	(-1.565)	(-1.791)	(-0.329)	(-0.779)	(-0.007)	(0.135)	(0.954)	(0.546)
Fund return	0.000	0.094	0.094	-0.089*	-0.105	0.166	0.027	-0.050	0.083	-0.032
	(0.001)	(0.608)	(0.768)	(-1.891)	(-1.008)	(1.010)	(0.219)	(-0.388)	(0.724)	(-0.627)
Intercept	0.578***	-0.278***	0.411***	0.037	0.393***	0.219***	0.390***	0.266***	0.451***	0.039
	(10.995)	(-2.825)	(5.130)	(1.102)	(8.231)	(2.816)	(4.742)	(4.825)	(6.885)	(1.052)
Cluster quarter effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,251	95,495	95,672	95,676	95,697	95,705	95,638	95,587	95,599	95,536
R-squared	0.1214	0.1269	0.0280	0.0184	0.0148	0.0142	0.0265	0.0065	0.0390	0.0086
Adjusted R-squared	0.121	0.127	0.0279	0.0183	0.0147	0.0141	0.0264	0.00636	0.0389	0.00847

In Table 5-3, I test Hypothesis Two by regressing risk betas calculated from different risk models on abnormal cash holdings and other controls. In my regression specifications, control variables include fund size, fund family size, fund age, total expense ratio, lagged flows, return volatility and fund return. The dependent variables are risk betas measured as the risk loadings of fund returns. The main independent variable is abnormal cash holding measured as the rate of additional cash held by fund managers, following Simutin (2013).

In China, the results show that fund managers tend to tilt their portfolios towards stocks with higher investment (I/A) and profitability (ROE) risk exposure. In Panel A, the coefficient of the I/A risk factor on abnormal cash is 0.052 (t=1.805) and the coefficient of ROE risk factor on abnormal cash is 0.044 (t=2.182). For example, it suggests that 1% of abnormal cash leads to an average increase of 0.044% of risk loadings on the ROE risk factor. The coefficient of I/A risk is significant at the 10% level and the coefficient of the ROE risk factor is significant at the 5% level. The results indicate that higher asset growth and higher profitability companies might be primary targets of funds with high abnormal cash holdings. It might also indicate that fund managers increase their exposure to high beta stocks to obtain higher relative returns than their benchmarks (Christoffersen and Simutin, 2017).

In the US, the results show that fund managers tend to tilt their portfolios to stocks with lower systematic risk (MKT), lower momentum risk (UMD), lower profitability (ROE) risk, lower management (MGMT) risk and lower performance (PERF) risk. In Panel B Column 1, for the market risk factor (MKT), the coefficient of abnormal cash holdings is -0.175 (t=-2.46) which is significant at the 5% level. For example, it suggests that 1% of abnormal cash leads to an average decrease of 0.175% of risk loadings on the systematic risk factor. In Columns 4, 8, 9 and 10, for momentum (MGMT), profitability (ROE), management (MGMT) and performance (PERF) risk factors, the coefficients of abnormal cash holdings are -0.156 (t=3.374), 0.133 (t= 1.781), -0.207 (t=2.454) and -0.120 (t=2.297). The coefficients of the market risk factor, the MGMT risk factor and the PERF risk factor are significant at the 5% level. The coefficient of the momentum risk factor is significant at the 1% level, and the coefficient of the ROE risk factor is significant at the 10% level. The results indicate that fund managers tend to reduce their overall risk if they have more cash by decreasing their portfolios comprising companies with higher systematic risk (MKT), higher momentum risk (MOM), higher profitability risk (ROE), high management risk (MGMT) and higher company performance risk (PERF).

In sum, fund managers in China show more aggressive strategies and trade in asset growth risk and profitability risk, while US fund managers tend to reduce their risk exposures, especially market risk. The results demonstrate the different risk-incentives of fund managers between China and the US. This is also consistent with Frazzini and Pedersen (2014) as higher beta stocks tend to have lower alphas and Sharpe ratios than low beta ones. High-beta strategies can increase the risk for portfolios that decreases investor incentives to purchase or hold fund shares. However, high-beta strategies may lead to higher returns to compensate for investors' risk-taking. Fund managers should find a tradeoff based on risk-beta strategies in their asset selection.

5.7 Fund Flows and Abnormal Cash Holdings

How do investors react to funds with higher abnormal cash holdings? To examine the effect of abnormal cash holdings on investors' fund decision, I regress fund flows on abnormal cash holdings and a group of control variables including fundamental fund characteristics, active investment factors, risk alphas and risk betas.[28]

$$Flow_{i,t} = \beta_0 + \beta^{cash} * abnormal\ cash_{i,t-1} + \beta_i^{alpha} * alpha_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{fundamental} * fundamental_{i,t-1} + \varepsilon_{i,t}$$

(Eq. 5-3)

Table 5-4 ACH and Future Fund Flows

This table presents the regressions of fund flows on abnormal cash holdings and other controls. The dependent variable is quarterly fund flows. The main independent variable is abnormal cash holding (ACH). Other control variables include risk-adjusted alphas, risk betas, active investment factors and fundamental fund characteristics. Risk-adjusted alphas and risk betas are calculated from the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model, the Fama-French five-factor model and the Q-factor model with 24-month rolling window regressions. Active investment factors include fund diversification, industry concentration index, reliance on public information, fund-report attention, active share, and return gap. Fundamental fund characteristics include log of fund size, log of fund family size, fund age, total expense ratio, lagged fund flow, prior 12-month return volatility and prior 12-month flow volatility.

$$Flow_{i,t} = \beta_0 + \beta^{cash} * abnormal\ cash_{i,t-1} + \beta_i^{alpha} * alpha_{i,t-1} + \sum \beta_i^{risk} * risk\ factor_{i,t-1} + \sum \beta_i^{active} * active\ factor_{i,t-1} + \sum \beta_i^{fundamental} * fundamental_{i,t-1} + \varepsilon_{i,t} \quad (5\text{-}3)$$

I run double-clustered regressions to get the coefficients. Regarding the regressions, cluster effects are studied with standard errors clustered at both the fund level and the quarter level. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

[28] Due to the availability of fund holdings data, I exclude active investment factors in the flow regression of the US market in this section.

Table 5-4 (continued)

Panel A: China funds

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ACH	0.020***	0.165**	0.016**	0.163**	0.021***	0.141**	0.162**
	(2.836)	(2.317)	(2.163)	(2.382)	(3.403)	(2.079)	(2.435)
Fund size (log)	-0.021***			-0.027***	-0.027***		-0.031***
	(-4.700)			(-3.697)	(-5.979)		(-4.234)
Family size (log)	0.013**			0.009**	0.015***		0.012**
	(2.205)			(2.003)	(2.657)		(2.122)
Age (log)	-0.014			0.000	0.001		0.013
	(-1.079)			(0.032)	(0.108)		(1.104)
Total expense ratio	-0.406*			-0.083	-0.313*		-0.043
	(-1.943)			(-0.400)	(-1.651)		(-0.205)
Lagged flow	0.160***			0.156***	0.151***		0.138***
	(4.387)			(3.703)	(4.050)		(3.471)
Return volatility	0.623***			0.766**	0.700***		1.003***
	(2.821)			(2.513)	(3.804)		(4.336)
Flow volatility	-0.003			0.003	-0.027		0.009
	(-0.090)			(0.096)	(-0.938)		(0.331)
Diversification		0.013*		0.026***		0.004	0.026***
		(1.800)		(4.199)		(0.617)	(3.873)
Industry concentration index		0.376***		0.204*		0.219*	0.156
		(3.109)		(1.808)		(1.728)	(1.555)
Reliance on public information		0.048**		0.018		0.035**	0.011
		(2.470)		(1.027)		(2.359)	(0.651)
Fund-report attention		0.013		0.030		0.015	0.033*
		(0.605)		(1.313)		(0.781)	(1.648)
Active share		-0.068		-0.058		-0.009	-0.014
		(-1.616)		(-1.556)		(-0.203)	(-0.362)
Return gap		0.000		0.048		-0.011	0.027
		(0.004)		(1.359)		(-0.281)	(0.792)
CAPM alpha			3.734***		3.355***		2.059***
			(5.213)		(5.992)		(3.645)
Beta MKT FF4			0.088***		-0.008	0.034	-0.056
			(3.930)		(-0.274)	(0.959)	(-1.496)

Table 5-4 (continued)

Beta SMB FF4			0.067***		0.034*	0.069***	0.031
			(3.295)		(1.697)	(2.708)	(1.395)
Beta HML FF4			-0.027*		0.000	0.012	0.029**
			(-1.910)		(0.021)	(0.612)	(2.175)
Beta UMD FF4			-0.001		0.007	0.013	0.018
			(-0.089)		(0.482)	(0.469)	(0.800)
Beta CMA FF5			0.027***		0.022**	0.020	0.011
			(3.055)		(2.473)	(1.428)	(0.792)
Beta RMW FF5			-0.010		-0.003	-0.003	0.004
			(-1.432)		(-0.422)	(-0.213)	(0.420)
Beta I/A QF			-0.024		-0.009	-0.013	-0.010
			(-1.549)		(-0.642)	(-0.600)	(-0.611)
Beta ROE QF			-0.007		-0.015	-0.007	-0.019
			(-0.517)		(-1.343)	(-0.401)	(-1.474)
Intercept	0.156	-0.156*	-0.116***	0.085	0.182	-0.157	0.089
	(1.353)	(-1.787)	(-4.858)	(0.908)	(1.543)	(-1.604)	(0.890)
Cluster quarter effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,249	5,145	11,682	4,831	10,829	4,845	4,647
R-squared	0.0469	0.0076	0.0232	0.0545	0.0628	0.0152	0.0698
Adj. R-squared	0.0462	0.00629	0.0224	0.0517	0.0613	0.0122	0.0652

Panel B: US Funds

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ACH	0.161***	0.156**	0.178***	0.176***	0.169***	0.183***
	(2.578)	(2.531)	(3.110)	(2.961)	(2.608)	(2.959)
CAPM alpha		7.912***		5.347***	7.639***	5.219***
		(11.824)		(10.644)	(13.126)	(11.200)
Beta MKT CAPM		-0.001		0.006		
		(-0.100)		(0.799)		
Beta MKT FF4					-0.023	0.004
					(-1.412)	(0.252)
Beta SMB FF4					-0.009*	-0.008
					(-1.814)	(-1.634)
Beta HML FF4					0.002	-0.001
					(0.190)	(-0.225)

Table 5-4 (continued)

Beta UMD FF4					0.049***	0.012
					(2.859)	(1.051)
Beta CMA FF5					-0.000	-0.002
					(-0.051)	(-0.612)
Beta RMW FF5					0.006	0.003
					(0.911)	(0.761)
Beta I/A QF					0.000	-0.001
					(0.029)	(-0.107)
Beta ROE QF					-0.004	0.006
					(-0.278)	(0.834)
Beta MGMT MF					0.001	0.006
					(0.153)	(0.720)
Beta PERF MF					-0.020	-0.007
					(-1.007)	(-0.544)
Fund size (log)			-0.010***	-0.012***		-0.012***
			(-6.272)	(-6.967)		(-7.004)
Family size log			0.005***	0.005***		0.005***
			(5.667)	(5.929)		(6.000)
Age			-0.015***	-0.012***		-0.013***
			(-6.844)	(-5.557)		(-5.540)
Total expense ratio			-0.209	-0.118		0.082
			(-0.589)	(-0.322)		(0.224)
Lagged flow			0.378***	0.338***		0.336***
			(21.402)	(20.538)		(20.235)
Return volatility			-0.254**	-0.499***		-0.433***
			(-2.568)	(-4.726)		(-4.323)
Flow volatility			0.011	0.012		0.012
			(1.449)	(1.467)		(1.437)
Intercept	0.021***	0.021**	0.173***	0.190***	0.044***	0.184***
	(5.876)	(1.964)	(6.683)	(7.398)	(2.845)	(7.748)
Cluster quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,449	99,313	95,778	94,045	98,701	93,724
R-squared	0.0002	0.0072	0.0407	0.0433	0.0074	0.0431
Adj. R-squared	0.000171	0.00716	0.0406	0.0432	0.00730	0.0430

In Table 5-4, the results show that higher abnormal cash holdings can significantly attract money inflows in both the China and US markets. The dependent variables for both markets are quarterly fund flows. It is measured as the rate of asset growth (fund size) in one quarter, which is net of fund returns. The main independent variables are abnormal cash which is the rate of additional cash in fund portfolios. In Panel A, the coefficients of abnormal cash holdings are positive and significant, ranging from 0.02 (t=2.836) to 0.165 (t=2.317) across regressions 1-7. For example, in Column 7, it suggests that 1% of abnormal cash leads to an average increase of 0.162% (t=2.435) of fund flows. The coefficient of abnormal cash holdings is significant at the 1% level in Columns 1 and 5, and it is significant at the 5% level in other columns. In addition, investors tend to purchase funds with greater diversification and higher CAPM alpha. In Column 7, diversification and CAPM alpha significantly drive fund flow with a coefficient of 0.026 (t=3.873) and 2.059 (t=3.645) respectively. The coefficients of them are both significant at the 1% level. Moreover, funds with small size, large fund family size, higher lagged flows and higher return volatility can attract more capital inflows. The log of fund family size, lagged flow and return volatility show positive coefficients of 0.012 (t=2.122), 0.138 (t=3.471) and 1.003 (t=4.336), while the log of fund size shows a negative coefficient of -0.031 (t=-4.234). The coefficients of lagged flow, return volatility and fund size are significant at the 1% level, and the coefficient of fund family size is significant at the 5% level.

For Panel B, the coefficient of US abnormal cash holdings is significant and positive, ranging from 0.161 (t=2.578) to 0.183 (t=2.959). For example, 1% of abnormal cash is associated with an average increase of 0.183% of fund flows. The coefficient of abnormal cash holdings in Column 2 is significant at 5% level, and its coefficients are significant at the 1% level in other columns. In addition, US investors tend to purchase funds with higher CAPM alpha. It shows a positive coefficient of 5.219 (t=11.2) in Column 6, which is significant at the 1% level. Moreover, for fund characteristics, funds with smaller size, larger fund family size, younger age, higher lagged flow and lower return volatility enjoy higher money inflows. The log of fund family size and lagged flow show positive coefficients of 0.005 (t=6) and 0.336 (t=20.235), while the log of fund size, fund age and return volatility show negative coefficients of -0.012 (t=-7.004), -0.013 (t=-5.540) and -0.433 (t=4.323) respectively. These coefficients are significant at the 1% level.

In sum, the result suggests that investors treat abnormal cash holding as an important signal in their fund decisions in both China and the US. The findings are consistent with Chordia (1996) and Chernenko and Sunderam (2016) as fund managers conduct liquidity transformation in cash management to reduce the price impact of their portfolios. It may also provide evidence that flow-performance sensitivity is stronger in funds with illiquid assets (Chen, Goldstein and Jiang, 2010). Moreover, CAPM alpha also plays an essential role in driving flows in both markets, since it shows positive coefficients with strong significance in both China and the US. Furthermore, investors in both China and the US are aware of scale-decreasing returns (Chen et al., 2004; Pollet and Wilson, 2008) and the smart money effect (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008).

5.8 Fund Performance and Abnormal Cash Holdings

To examine whether abnormal cash holdings can predict better fund performance, I construct fund portfolios and sort them by abnormal cash holdings (ACH). Then, I double sort them by abnormal cash holdings (ACH) and the lagged fund flows. Risk-adjusted alphas are calculated for each portfolio after formation.

Table 5-5 ACH and Fund Performance

This table presents the results from single portfolio sorts based on abnormal cash holdings (ACH) and double portfolio sorts based on funds' ACH and fund flows. The row "High - Low" reports the difference between returns from quintile 5 and quintile 1. In Panel A, I sort funds into quintiles based on their ACH. Returns are adjusted with the CAPM, the Fama-French model (FF3) and the Fama-French-Carhart (FF4) model. In Panel B, I sort funds into quintiles in each month and form portfolios based on their abnormal cash holdings (ACH) and fund flows. Value-weighted portfolios are formed and held for 36 months. Returns are adjusted with the Fama-French-Carhart model. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Panel A: Single sorting by ACH

	China			US		
	CAPM	FF3	FF4	CAPM	FF3	FF4
Portfolio						
1 Low abnormal cash	0.244%	0.197%	0.351%	-0.061%	-0.089%	-0.098%
2	0.309%	0.237%	0.386%	-0.074%	-0.086%	-0.096%
3	0.293%	0.169%	0.303%	-0.053%	-0.059%	-0.069%
4	0.202%	0.108%	0.254%	-0.057%	-0.073%	-0.081%
5 High abnormal cash	0.241%	0.153%	0.293%	-0.015%	-0.040%	-0.051%
High - Low	-0.003%	-0.044%	-0.058%	0.059%	0.065%	0.060%
t-stat	(-0.05)	(-0.75)	(-1.09)	(1.86)*	(2.02)**	(1.85)*

Panel B: Double sorting by ACH and fund flows
China Funds

Portfolio	1 Low fund flows	2	3	4	5 High fund flows	High -Low	*t*-stat
1 Low abnormal cash	0.37%	0.18%	0.34%	0.49%	0.54%	0.17%	(0.92)
2	0.38%	0.36%	0.33%	0.38%	0.44%	0.06%	(0.77)
3	0.38%	0.31%	0.21%	0.41%	0.25%	-0.13%	(-1.94)*
4	0.28%	0.28%	0.22%	0.30%	0.37%	0.10%	(1.47)
5 High abnormal cash	0.33%	0.15%	0.23%	0.25%	0.38%	0.04%	(0.4)
High - Low	-0.04%	-0.03%	-0.12%	-0.24%	-0.16%		
t-stat	(-0.22)	(-0.25)	(-1.66)	(-2.74)**	(-1.62)		

Table 5-5 (continued)
US Funds

Portfolio	1 Low fund flows	2	3	4	5 High fund flows	High -Low	*t*-stat
1 low abnormal cash	-0.13%	-0.10%	-0.10%	-0.11%	-0.12%	0.013%	(0.26)
2	-0.10%	-0.10%	-0.10%	-0.08%	-0.11%	-0.013%	(-0.24)
3	-0.10%	-0.11%	-0.11%	-0.07%	-0.11%	-0.004%	(-0.07)
4	-0.07%	-0.08%	-0.09%	-0.07%	-0.13%	-0.059%	(-1.2)
5 High abnormal cash	-0.08%	-0.09%	-0.04%	-0.07%	-0.17%	-0.093%	(-1.41)
High - Low	0.05%	0.01%	0.06%	0.04%	-0.05%		
t-stat	(2.42)**	(1.19)	(2.45)**	(1.36)	(-1.98)*		

In Table 5-5, consistent with Hypothesis Three, in Panel A, it shows that funds with higher abnormal cash holdings can outperform their peers in the US market. In the US, a long-short portfolio sorted by abnormal cash holdings offers a positive and significant CAPM alpha of 0.059% (t=1.86), a FF3 alpha of 0.065% (t=2.02) and a FF4 alpha of 0.06% (t=1.85). The coefficients of CAPM alpha and FF4 alpha are significant at the 10% level, and the coefficient of FF3 alpha is significant at the 5% level. In China, a long-short portfolio sorted by abnormal cash holdings offers insignificant return spread at the 10% level. It suggests that strategies of abnormal cash holdings are more profitable in the US market.

In Panel B, I further double sort fund portfolios by lagged fund flows and abnormal cash holdings. In China, the performance predictability of ACH is affected by lagged fund flows. Funds with high lagged fund flows seem to demonstrate less skill in abnormal cash holding. It shows a negative and significant alpha of -0.24% (t=-2.74) at the 1% level in the fourth flow quintile. It implies that fund managers with price pressure from fund flows (Coval and Stafford, 2007) might not make better decisions with abnormal cash.

In the US, the fund portfolio has a significant long-short FF4 alpha of 0.05% (t=2.42) at the 5% level at the lowest flow quintile. Also, the alphas of spread portfolios keep positive when flow increases from the lowest flow quintile to the medium flow quintile. It offers a FF4 alpha of 0.06% (t=2.45) at the medium (or third) flow quintile, which is significant at the 5% level. If it exceeds the medium flow quintile, the spread of ACH decays its significance or even shows some evidence to reverse in the highest flow quintile, which has a significant FF4 alpha of -0.05% (t=1.98) at the 5% level. The results show that, below the medium level of fund flow, if funds with higher money flows tend to hold more abnormal cash, they are more likely to outperform their peers. The results indicate that, first, fund managers holding large abnormal cash might be good at market timing. When new investment opportunities appear, they take these opportunities and purchase these stocks quickly with abnormal cash (Yan, 2013; Simutin, 2013). Second, fund managers holding large abnormal cash might benefit from mitigating their price pressure. When funds experience money outflows, they might utilize abnormal cash to satisfy redemption costs (Chordia, 1996). Third, funds with the highest ACH which could be as a result of extreme inflows, they might purchase too many of their existing stocks at an over-valued price (Simutin, 2013). This will finally erode their performance.

In sum, consistent with Hypothesis Three, liquidity management ability is also associated with smart money. As persistent money flows have a price impact on fund holdings (Wermers, 2003; Coval and Stafford, 2007; Lou, 2012), I provide evidence that fund managers should actively control their cash holdings in dealing with persistent flows and that there is a tradeoff between persistent money flows and reducing price impact by holding abnormal cash. Also, I find that the performance predictability of abnormal cash holdings interacts with the smart money effect, especially in the US market.

5.9 Conclusion

In the study, I examine the determinants of cash holdings and explore how fund managers with higher abnormal cash holdings adjust their future portfolio in the China and US markets. First, I find that cash holdings in China are more affected by non-risk factors such as fund size, fund age, return volatility, fund-report attention and active share, while in the US risk factors like market beta, size risk beta (SMB) and value risk beta (HML) show relative higher explanatory power for cash holdings. Second, I provide empirical evidence that fund managers with higher abnormal cash holdings tend more towards reducing their risk exposure in their future investments in the US, while fund managers in China shows less sensitivity to systematic risk but tend to trade in investment (I/A) and profitability risk (ROE) from Hou, Xue and Zhang (2014). Finally, consistent with Simutin (2013) and Graef et al. (2018), I confirm that funds with high abnormal cash holdings outperform those with low abnormal cash holdings by a monthly FF3 alpha of 0.065% (t=2.02) in the US. I also find that the abnormal cash holdings' ability to predict fund performance is stronger in funds under the medium level of lagged flows. It suggests that a combination of smart money and better liquidity management skills could be an important signal to sophisticated investors in fund selection.

Overall, this study sheds light on the understanding of superior management skills based on abnormal cash holdings in China and the US. It gives more explanations of the decision mechanisms of fund managers regarding cash management as US fund managers are more risk-sensitive while Chinese fund managers are more affected by non-risk factors. It confirms that abnormal cash holdings can signal superior funds in the US and provides evidence that abnormal cash holdings lead to lower beta strategies in future investments in the US than in China. Fund managers should find a tradeoff between holding cash and investing. Due to data availability, the analysis is limited to apply active skill measures in the US market. Further studies could include active measures with more comprehensive US holdings data. Alternative risk factors could also be employed to explore investment strategies that follow above risk beta analysis.

Chapter 6 Which Active Funds are Smart? Digesting Flow-Induced Trading on Stock Return Anomalies and Fund Performance

6.1 Introduction

If fund managers intend to transact their portfolios when experiencing capital inflows or outflows, what is the subsequent performance of the stocks mutually held by these funds? A variety of studies focus on the trading decisions of fund managers and the institutional price pressure on their stock holdings under money inflows and outflows. Lou (2012) shows that flow-induced trading positively predicts short-term stock returns. Moreover, Anton and Polk (2014) find that extreme flows can strength the performance comovement of stocks mainly held by mutual funds. Frazzini and Lamont (2008) show that stock returns are negatively affected by counterfactual capital flows.[29] To understand the performance implications of fund flows, I follow Lou' method (2012) to investigate the mechanism of flow-driven trading in China.[30] This method allows us to measure the degree of flow-driven price pressure on stocks from funds with different levels of risk-adjusted performance and financial status.

Moreover, active fund managers may be more skilled in flow-motivated trading. On the one hand, the literature documents that superior funds with active skills do exist.

[29] The counterfactual assumption is that investors simply allocate their money to funds in proportion to fund size as proposed by Frazzini and Lamont (2008). When aggregate fund flow in the mutual fund market is positive, large funds will receive more money than small funds. Counterfactual flow on a stock is the difference between the flow calculated using the counterfactual assumption and actual flow.

[30] The study of flow-induced trading is based on quarterly mutual fund holdings. Since the data of US mutual fund holdings are not available and the effect of flow-induced trading has been studied in the US by Lou (2012), I focus on China in this chapter and compare to the US results studied by Lou (2012).

It states that funds investing in concentrated industries have a distinct investment style and outperform others (Kacperczyk, Sialm and Zheng, 2005); skilled fund managers should rely less on public information, and their trading has informational advantages (Kaperczyk and Seru, 2007); fund managers with higher return gap offer benefits to their investors in the form of hidden profit (Kacperczyk, Sialm and Zheng, 2008); fund managers with more diversification, especially in small-cap funds, tend to outperforms their peers (Pollet and Wilson, 2008); fund managers who invest with more deviation from the weights of their benchmarks indices tend to exhibit superior performance (Cremers and Petajisto, 2009); funds with lower R-squared based on common risk factors show greater selectivity and activity in investments and tend to outperforms their peers (Amihud and Genyenko, 2013).

On the other hand, the literature assumes that some mutual fund managers are unable to add value for investors. Institutional or individual investors can profit from distressed mutual funds based on predictable mutual fund flows and their holdings. Chen et al. (2008) show that the performance of long-short equity hedge funds is significantly higher when the mutual fund sector is in distress. Hedge funds profit from front-running before fire sales of distressed mutual funds. Dyakov and Verbeek (2013) argue that the publicly available mutual fund flows and mutual fund holdings of distressed mutual funds provide practical investment opportunities for sophisticated investors. Shive and Yun (2013) find that hedge funds can profit from the flow-induced trading of mutual funds. They earn more profits from more constrained mutual funds. Akbas et al. (2015) find that, on the aggregate fund flow level, mutual fund flows tend to exacerbate stock mispricing as studied by Stambaugh, Yu and Yuan (2012), while aggregate hedge fund flows tend to attenuate it and correct stock mispricing.

As Akbas et al. (2015) find that the aggregate level of mutual fund flows appears to be dumb and to exacerbate stock return anomalies, this study investigates the trading of active fund managers on the individual fund level. I examine whether active funds show skills to exploit stock return anomalies when experiencing money inflow or outflows. Fund-level flow-induced trading can also reveal the decision mechanisms of fund managers in China.

Furthermore, I study the subsequent performance of active funds affected by flow-induced trade. Coval and Stafford (2007) claim that funds with extreme outflows or inflows tend to liquidate their positions at a disadvantageous price or expand too much on their existing holdings. Lou (2012) shows that flow-induced trading can adequately explain the persistence of mutual fund performance and smart money effects. Based on the evidence that trading induced by capital flows is informative of fund performance, I reexamine the impact of flow-induced trade on mutual fund performance and study sources of predictability to see if they can be interactively explained by active skills. Moreover, as mutual fund flows are predictable (Gruber, 1996; Sirri and Tufano, 1998; Coval and Stafford, 2007), I confirm the robustness of flow-induced trade patterns with expected fund flows.

This study systematically investigates the flow-induced trading mechanism in China, and it interactively studies flow-induced trade from the perspective of active management skills (Kacperczyk, Sialm and Zheng, 2008; Pollet and Wilson, 2008; Cremers and Petajisto, 2009) and stock return anomalies (Stambaugh, Yu and Yuan, 2012). I have the following key findings:

First, flow-induced trade positively predicts the stock returns of fund holdings in China. If a stock is primarily purchased by mutual funds, the risk-adjusted return is greater than a stock massively sold by mutual funds. A flow-induced pattern persistently drives up the stock price with a little reversal in a two-year period. By constructing a long-short stock portfolio based on flow-induced trading (FIT), it generates an annualized value-weighted four-factor alpha of 4.2% (t=2.7) over a one-year horizon. Notably, return predictability is more pronounced in the short term (three months). Consistent with Coval and Stafford (2007) and Lou (2012), mutual funds experiencing large fund inflows or outflows have price pressure on their existing holdings. Fund managers who engage in flow-motivated purchases push up the stock prices of their holdings, while fund managers who liquidate their holdings under redemptions lower their stock prices. This effect of flow-induced trade is more pronounced in the short term in China as well as in the US.

Second, the flow-induced trade of skilled fund managers appears to be relatively smart, and fund managers may exploit stock return anomalies when experiencing money inflows or outflows. Active fund managers show evidence to tilt their portfolio towards higher ranks (undervalued stocks) of composite signals of the overall mispricing metric based on nine anomalies studied by Stambaugh, Yu and Yuan (2012).

I demonstrate the existence of anomaly returns based on the overall mispricing metric in China. This offers a value-weighted four-factor alpha of 2.412% (t= 8.38) per month. The return spread of individual anomalies, including total accruals, gross profitability, asset growth, return on assets, net stock issues, momentum and composite anomalies, including non-investment anomalies, investment anomalies, three anomalies documented prior to 1997 and six anomalies from 1997 forward, show positive and significant return spreads over 3-month to 12-month horizons.

In addition, I find that skilled funds with a higher return gap, higher industry concentration appear to trade on the overall mispricing metric, the composite signals of non-investment anomalies, including return on assets, gross profitability, net stock issues, total accruals and momentum. Also, well-diversified funds may trade on the overall mispricing metric. Moreover, active fund managers appear to trade on the prior to 1997 anomalies. The results are consistent with the literature studying the active skills of fund managers (Kacperczyk, Sialm and Zheng, 2005; 2008; Kaperczyk and Seru, 2007; Pollet and Wilson, 2008; Cremers and Petajisto, 2009). Superior active mutual funds may reward investors with anomaly returns, and they might not be dumb as the literature assumes (Akbas et al., 2015).

Third, the flow-induced mechanism is predictive of short-term fund performance. The return spread of a long-short fund portfolio based on FIT has a value-weighted four-factor alpha of 0.885% (t=2.77) per month or 10.62% (t=2.77) per annum over a 3-month horizon. Investors may identify flow-induced trade as a predictor to select funds. In addition, the double sorting of funds by flow-induced trade and active investment factors show that return gap and active share may partially explain performance predictability. Consistent with Lou (2012), this result supports the flow-induced mechanism accounting for the short-term persistence of mutual fund performance in China as well as in the US, since past winning funds can attract money inflows and then invest them in their existing holdings, which drives up their stock price.

Fourth, as mutual fund flows are predictable, I utilize predictable fund flows to construct FIT and further check the robustness of the performance predictability of it. I calculate the expected flow induced-trading at the individual fund level. The results are consistent as expected flow-induced trading (EFIT) also positively predicts fund performance. Funds with expected flow-induce purchases offer significantly higher performance than funds with expected flow-induced selling. In addition, active skills, including return gap and active share, also partially explain the performance predictability of the expected flow-induced mechanism. The results are robust and consistent with the analysis of flow-induced trade.

My study contributes to a strand of literature studying institutional price pressure (Coval and Stafford, 2007; Lou, 2012). First, I confirm that the flow-induced mechanism exists, and it drives up stock returns and fund performance in the developing market of China. Sophisticated investors can consider profitable patterns of flow-induced trade in their stock selection and fund picking. As for mutual fund managers, they should reconsider their stock picking and market timing under money inflows or outflows, since superior active managers trade more patiently (Yan, 2006; Cremers and Pareek, 2016).

Second, my study contributes to the literature identifying the active skills of fund managers from the perspective of exploiting stock mispricing. Consistent with Stambaugh, Yu and Yuan (2012), it offers empirical evidence of anomaly returns in China. I show that flow-induced trade is a positive predictor of future fund performance as active fund managers trade in the right direction of stock return anomalies. It indicates that the trades of skilled fund managers are relatively smart, and they may trade in undervalued stocks based on anomalies (Stambaugh, Yu and Yuan, 2012). It provides more evidence that active fund management including industry concentration (Kacperczyk, Sialm and Zheng, 2005), return gap (Kacperczyk, Sialm and Zheng, 2008), fund diversification (Pollet and Wilson, 2008) and active share (Cremers and Petajisto, 2009) does add value for investors.

Third, my study is related to papers studying the smart money effect (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). My findings enrich our understanding of the consequences of smart money. As smart money flows in, fund managers vary in their trading strategies that they own active investment skills differently. It supports the existence of smart money that funds receiving high money flows subsequently outperform their low flows peers, and the smart money effect is more pronounced in funds exhibiting higher active skills. Superior fund performance can be identified as the interaction between the two dimensions of sophisticated investors and active fund managers.

The rest of this chapter is organized as follows. Section 6.2 reviews relevant literature. Section 6.3 develops hypotheses. Section 6.4 describes data sources and methodology. Section 6.5 present empirical results. Section 6.6 concludes.

6.2 Literature Review

Money flows to mutual funds have been labelled as "smart money" and "dumb money" under different rationales by scholars. Investors should follow smart money and keep away from dumb money. I review the literature on how scholars judge mutual fund flows and the implications of fund flows for stock returns and fund performance.

6.2.1 Smart Money vs Dumb Money

The literature finds that institutional investors can trade on the price pressure of mutual funds. It documents that long-short equity hedge funds show higher returns when the mutual fund sector is in distress. Hedge funds profit from front-running before fire sales of distressed mutual funds (Chen et al., 2008). Trading strategies based on predictable fire sales of mutual funds generated a 0.5% monthly abnormal return from 1990-2010. Publicly available mutual fund flows and mutual funds' holdings of distressed mutual funds provide practical investment opportunities for sophisticated investors (Dyakov and Verbeek, 2013). Mutual funds and short-sellers conduct opposite trades; when mutual funds increase their net purchases, short-sellers increase their net short-selling activities. It suggests that short-sellers profit from liquidity provisions related to mutual fund flows (Arif, Ben-Rephael and Lee, 2015).

In addition, a growing body of literature comparatively studies hedge fund flows and mutual fund flows. Shive and Yun (2013) find that hedge funds are able to profit from flow-induced trading by mutual funds. They have more patient capital to trade on forecastable mutual fund flows. One unit increase in the standard deviation of the trading by hedge fund based on mutual fund flows is associated with a 0.9% annualized four-factor alpha. Akbas et al. (2015) find that aggregate mutual fund flows tend to exacerbate the stock return anomalies studied by Stambaugh, Yu and Yuan (2012), while aggregate hedge fund flows tend to attenuate them. They label hedge fund flows as smart money, while give mutual fund flows a dumb label. Barber, Huang and Odean (2016) argue that hedge fund managers may buy or sell mutual funds based on whether the skills of mutual fund managers are underpriced or overpriced. Moreover, hedge fund managers can replicate the trading strategies of mutual fund managers. So, hedge fund flows also indicate the risk models that investors employ. In this case, by studying both mutual fund flows and non-mutual fund flows (hedge funds), this might indicate the true asset pricing model studied by Berk and Van Binsbegen (2016). However, limited studies have explored whether money is smart among different active mutual funds.

My study links mutual fund flow studies to recent literature on active skills. The literature documents that the active skills of fund managers exist. Active share positively predicts performance. Funds with high active share also show strong performance persistence (Cremers and Petajisto, 2009). Also, skilled fund managers have an informational advantage and construct their portfolios with distinct investment strategies in several industries. A high industry concentration indicates superior performance (Kacperczyk, Sialm and Zheng, 2005). Moreover, experienced managers are able to provide investors with hidden profits or reduce extra costs. The return gap between fund returns and the returns calculated from stock holdings can imply superior fund performance (Kacperczyk, Sialm and Zheng, 2008). In addition, experienced fund managers are less sensitive to the changes in analysts' recommendations. Less reliance on public information indicates higher management skill (Kacperczyk and Seru, 2007). Finally, skilled managers diversify their portfolios, and the superior performance of diversified investments is more pronounced in small funds (Pollet and Wilson, 2008). I fill this literature gap by investigating the sophisticated mutual funds identified by these active skills to examine whether they have the ability to exploit the stock return anomalies studied by Stambaugh, Yu and Yuan (2012).

6.2.2 Mutual Fund Flows and Performance Predictability

From the perspective of fund flows and stock return predictability, earlier literature identifies a positive relation between aggregate fund flows and market returns. (Warther, 1995; Edelen and Warner, 2001). Higher counterfactual fund flows indicate lower stock returns (Frazzini and Lamont, 2008). Large arbitrage flows reduce the future returns of capital market anomalies and improve market efficiency, and vice versa (Akbas et al., 2016). Aggregate hedge fund flows attenuate stock return anomalies while aggregate mutual fund flows exacerbate them (Akbas et al., 2015). The literature provides evidence that fund flows do affect the returns of stocks which might offer a profitable pattern for institutional or retail investors. Consistent with the literature, I take the method of Lou (2012) and construct a long-short stock portfolio based on flow-induced trade (FIT). A long-short strategy based on FIT can be utilized by sophisticated investors to study performance implications.

From the perspective of trading in lagged fund flows, scholars find that funds with higher past fund flows tend to have higher risk-adjusted alphas than those funds with lower past fund flows. It indicates that the smart money effect exists. More specifically, Gruber (1996) finds that investors have the ability to pick well-performing funds and benefit from supplying new cash flows. In addition, Zheng (1999) confirms the smart money effect with a large fund dataset. She finds that the smart money effect is short-lived, not attributable to a momentum strategy and more pronounced in small funds. Furthermore, Keswani and Stolin (2008) find that the smart money effect robustly exists in the UK even after controlling for momentum factors, and it is caused by the money inflows (buying), not outflows (selling), of both individual and institutional investors. Moreover, Yu (2012) finds that the existence of the smart money effect in US small funds is mainly attributable to the market-timing ability of investors. The evidence is robust after controlling for the momentum factor. My study is consistent with this literature as the money flows of sophisticated investor are predictive of the future fund performance and also motivate active fund managers to trade in the right direction of stock return anomalies.

6.3 Hypotheses

To study the return predictability of flow-induced trade and its relation to active skills and stock return anomalies, I develop three hypotheses based on evidence from prior literature.

Hypothesis One: Flow-induced trade can generate a persistent pattern that drives up the stock returns of fund holdings in China.

Coval and Staffod (2007) find that flow-induced buying can persistently result in a price impact on their existing holdings, and flow-induced selling drives price below their fundamental value. Also, Lou (2012) finds that flow-induced trading positively predicts stock returns. He also finds that flow-induced trading can fully explain the smart money effect and the persistence of mutual fund performance in the US. I hypothesize that the trading of fund managers is informative about the returns on their stock holdings when they are experiencing large inflows or outflows in China. If investors can understand the mechanism of price impact from fund flows, they might make profits by trading against this flow-induced pattern. In addition, I seek to determine whether the return pattern reverses in the long run. With a comprehensive mutual fund holding database for the China fund market, I can systematically examine the flow-induced price impact on funds' holdings and study their subsequent return patterns. Then, I have the first hypothesis.

Hypothesis Two: Skilled fund managers have the ability to exploit stock return anomalies when funds experience money inflows or outflows.

The literature documents that the active skills of fund managers do exist and lead to better fund performance. Kacperczyk, Sialm and Zheng (2005) find that funds that invest in concentrated industries have a distinct investment style that can outperform peer funds; Kacperczyk and Seru (2007) show that skilled managers have more private information and so their trading should rely less on public information; Kacperczyk, Sialm and Zheng (2008) document that the return gap between fund returns and the returns computed from fund holdings can act as a predictor of fund performance. A higher return gap indicates greater skill and more hidden profit; Pollet and Wilson (2008) document that greater diversification is associated with better fund performance. It is more pronounced among small size funds. These studies support active skills adding value for investors.

In contrast, Akbas et al. (2015) find that, on the aggregate level, mutual funds tend to exacerbate stock return anomalies by longing overvalued stocks and shorting undervalued ones, while hedge funds tend to exploit anomalies and trade in the right direction. However, they do not focus on fund-level trading to study the ability of fund managers in details. Active skills studies show that superior fund managers have an informational advantage (Kacperczyk, Sialm and Zheng, 2005; 2008; Kacperczyk and Seru, 2007) and better stock selection skills (Cremers and Petajisto, 2009; Amihud and Goyenko, 2013) in their trades. These skilled fund managers should be aware of the investment opportunities of stock return anomalies. I expect superior fund managers, measured by active skills to have the ability to exploit anomalies, especially when they are motivated by money flows and have the second hypothesis.

Hypothesis Three: Flow-induced trade on the fund-level also indicates better fund performance in the short term and the performance predictability of the flow-induced mechanism is robust with expected flows.

If a fund's existing holdings are also held by other funds with larger money inflows or outflows, the trade motived by fund flows that drive up stock returns might also increase the fund's performance. As Lou (2012) finds that US funds with higher expected flow-induced trade significantly outperform their peers with low expected flow-induced trade, I expect that the funds themselves will also have a short-term performance increase related to flow-induced trade. I hypothesize that flow-induced trading on the individual fund level is predictive of short-term fund performance in China. A large body of literature contributes to the methods to identify superior fund performance. It includes CAPM alpha from Jensen (1968); benchmark-free performance measurement from Grinblatt and Titman (1993); the momentum-based model from Carhart (1997); the characteristic timing and characteristic selectivity approach from Daniel, Grinblatt, Titman and Wermers (1997); conditional skills in different business cycles from Kacperczyk, Nieuwerburgh and Veldkamp (2014); measuring skills with added assets of fund managers from Berk and Binsbergen (2015); holding-based measurements with stochastic factors adjustment from Ferson and Mo (2016). If the flow-induced mechanism persistently affects fund performance, investors can utilize forecastable flows with flow-induced trading to pick funds. An expected flow-induced trade pattern can also confirm the robustness of the findings. Then, I propose the third hypothesis.

6.4 Data and Methodology

I obtain quarterly fund holdings data from the CSMAR fund database for the period 2007-2016.[31] I retain China domestic equity funds and exclude fixed-income funds, ETF, money market funds, index funds and commodities funds. The sample has 596 distinct equity funds from 2007-2016. Monthly stock prices are obtained from the CSMAR stock database. I follow the definition of fund flows from Coval and Stafford (2007) and Barber, Huang and Odean (2016).

$$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t})}{TNA_{i,t-1}}$$

(Eq. 6-1)

$TNA_{i,t}$ is the total net assets of fund *i* in quarter *t*, $RET_{i,t}$ is the return on net asset value (NAV) of fund *i* in quarter *t*, which is obtained from quarterly reports from the CSMAR Chinese mutual fund database.

[31] The sample includes all the semi-annual fund holding data from the start of the CSMAR Chinese database. The Fama-French risk factors in China are also obtained from it.

Table 6-1 Summary Statistics for Flow-Induced Trade

This table reports summary statistics for fund trading, portfolio-level anomalies, fund characteristics, fund performance and active investment factors. Fund trading includes flow-induced trade calculated using actual fund flow, expected flow-induced trade calculated using predicted flows. Stock return anomalies includes value-weighted nine anomalies based on Stambaugh, Yu and Yuan (2012), the overall mispricing metric is the average mispricing rank based on nine anomalies, investment anomalies are the average rank of asset growth, composite equity issues, investment-to-assets and net operating assets. Non-investment anomalies are the average rank of the rest of the five anomalies. The prior to 1997 three anomalies are net stock issues, momentum and total accruals. The anomalies documented after 1997 are composite equity issues, net operating assets, gross profitability, asset growth, return on assets and investment-to-assets. Fund performance includes risk-adjusted alphas calculated from the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF) under 24-month rolling window regressions with monthly excess returns. Active investment factors include fund diversification, industry concentration index (ICI), reliance on public information (RPI) and return gap. Fundamental fund characteristics include fund size (in millions), family size per fund (in millions), fund age, lagged fund flow and prior 12-month return volatility. Descriptive statistics and Pearson correlations are reported in Panel A and Panel B respectively.

Variables	N	Mean	SD	Min	P25	Median	P75	Max
Fund trades								
Flow-induced trade	10917	-0.013	0.042	-0.554	-0.018	-0.008	-0.002	2.889
Expected flow-induced trade	10917	0.012	0.015	-0.080	0.002	0.009	0.019	0.296
Portfolio-level anomalies								
Overall mispricing metric (ranks)	10917	6.042	0.408	3.879	5.780	6.060	6.324	7.659
Non-investment anomalies (ranks)	10917	6.222	0.574	3.215	5.831	6.221	6.624	8.188
Investment anomalies (ranks)	10917	5.817	0.430	3.745	5.544	5.815	6.098	8.015
Three anomalies documented prior to 1997 (ranks)	10917	6.089	0.651	2.479	5.672	6.115	6.542	9.639
Six anomalies from 1997 forward (ranks)	10917	6.019	0.460	3.559	5.744	6.055	6.330	7.854
Total accruals (ranks)	10917	5.861	0.795	1.211	5.405	5.880	6.360	9.383
Net operating assets (ranks)	10917	5.160	0.945	1.001	4.601	5.237	5.803	9.027
Gross profitability (ranks)	10917	5.858	0.935	1.000	5.294	5.904	6.492	9.109

Table 6-1 (continued)

Asset growth (ranks)	10917	6.510	0.761	1.392	6.032	6.540	7.009	9.278
Return on assets (ranks)	10917	6.985	1.018	2.719	6.316	6.988	7.689	10.000
Investment-to-assets (ranks)	10917	6.087	0.671	1.935	5.660	6.106	6.525	9.537
Net stock issues (ranks)	10917	5.870	0.978	1.205	5.337	5.919	6.451	9.932
Composite equity issues (ranks)	10917	5.513	1.130	1.000	4.774	5.539	6.268	9.622
Momentum (ranks)	10917	6.535	1.394	1.529	5.581	6.606	7.568	10.000
Total accruals	10917	0.431	0.064	0.075	0.392	0.430	0.469	0.762
Net operating assets	10917	0.381	0.082	-0.091	0.327	0.380	0.439	0.687
Gross profitability	10917	0.373	0.180	0.009	0.225	0.356	0.501	1.140
Asset growth	10917	0.057	0.026	-0.077	0.040	0.055	0.071	0.272
Return on assets	10917	0.042	0.021	-0.005	0.025	0.041	0.057	0.126
Investment-to-assets	10917	0.016	0.011	-0.044	0.008	0.014	0.022	0.087
Net stock issues	10917	4.921	82.573	-0.775	0.051	0.833	2.136	5545.070
Composite equity issues	10917	-0.008	0.271	-0.965	-0.092	-0.030	0.042	9.993
Momentum	10917	0.420	0.575	-0.666	0.062	0.296	0.643	5.202
Fund characteristics								
Fund size	10917	3046.75	3920.94	9.34	422.91	1648.91	4108.96	44735.44
Fund age (months)	10917	68.692	32.187	12.000	42.000	63.000	90.000	180.000
Family size (per fund)	10917	26000.37	23576.69	19.79	8161.07	19291.13	35653.98	143731.00
Prior 12-month return volatility	10917	0.075	0.039	0.002	0.048	0.063	0.097	0.276
Fund flow	10917	0.001	0.472	-0.886	-0.093	-0.033	-0.003	9.764
Fund performance								
CAPM alpha	10917	0.31%	4.73%	-66.61%	-1.49%	0.55%	2.50%	27.16%
FF3 alpha	10917	0.29%	3.92%	-66.29%	-1.51%	0.31%	2.22%	21.72%
FF4 alpha	10917	0.53%	3.77%	-67.96%	-1.29%	0.37%	2.24%	25.25%
FF5 alpha	10917	0.46%	4.28%	-64.82%	-1.54%	0.37%	2.36%	33.00%
QF alpha	10917	0.07%	4.71%	-63.25%	-2.05%	0.19%	2.42%	29.29%
Active investment factors								
Diversification	8819	60.077	55.684	1	32	47	68	948
Industry concentration index	8704	0.040	0.029	0.002	0.021	0.033	0.049	0.222
Reliance on public information	7910	-0.147	0.524	-7.195	-0.159	-0.051	0.001	0.960
Return gap	8358	-0.102	0.233	-1.549	-0.164	-0.057	0.030	0.784
Active share	8107	0.116	0.087	0.00001	0.045	0.096	0.176	0.793

Table 6-1 (continued)

Panel B:

Correlation	Flow-induced trade	Expected flow-induced trade	Overall Mispricing metric	Fund size	Fund age (months)	Family size (per fund)	Prior 12-month return volatility	Fund flow	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Diver.	ICI	RPI	Return gap	Active share
Flow-induced trade	1.00	0.11	0.03	-0.01	-0.07	-0.01	0.09	0.35	0.13	0.05	0.01	-0.01	-0.02	-0.05	-0.03	-0.04	-0.09
Expected flow-induced trade	0.11	1.00	0.13	0.16	-0.01	0.09	0.19	0.03	0.12	0.13	0.06	0.07	0.04	0.02	0.02	0.13	0.05
Overall Mispricing metric	0.03	0.13	1.00	0.12	-0.08	0.01	-0.02	0.00	-0.01	0.00	-0.03	-0.05	-0.05	0.04	0.00	0.11	-0.06
Fund size	-0.01	0.16	0.12	1.00	0.02	0.36	-0.02	0.05	0.00	0.02	0.02	0.03	0.14	-0.02	0.03	0.03	0.21
Fund age (months)	-0.07	-0.01	-0.08	0.02	1.00	0.03	0.05	-0.06	0.00	-0.03	-0.02	-0.04	0.02	-0.02	-0.01	-0.01	-0.10
Family size (per fund)	-0.01	0.09	0.01	0.36	0.03	1.00	0.11	0.03	0.02	-0.01	0.00	-0.01	0.07	-0.01	0.00	0.04	0.00
Prior 12-month return volatility	0.09	0.19	-0.02	-0.02	0.05	0.11	1.00	0.07	0.10	-0.05	-0.02	-0.17	0.03	0.03	-0.02	0.14	-0.20
Fund flow	0.35	0.03	0.00	0.05	-0.06	0.03	0.07	1.00	0.01	-0.01	-0.02	-0.03	0.02	0.01	-0.04	-0.03	-0.04
CAPM alpha	0.13	0.12	-0.01	0.00	0.00	0.02	0.10	0.01	1.00	0.75	0.63	0.59	0.00	-0.02	0.00	0.18	0.01
FF3 alpha	0.05	0.13	0.00	0.02	-0.03	-0.01	-0.05	-0.01	0.75	1.00	0.90	0.87	0.00	0.00	0.00	0.12	0.07
FF4 alpha	0.01	0.06	-0.03	0.02	-0.02	0.00	-0.02	-0.02	0.63	0.90	1.00	0.83	-0.01	0.02	0.01	0.04	0.07
FF5 alpha	-0.01	0.07	-0.05	0.03	-0.04	-0.01	-0.17	-0.03	0.59	0.87	0.83	1.00	-0.01	0.02	0.03	-0.02	0.10
Diversification	-0.02	0.04	-0.05	0.14	0.02	0.07	0.03	0.02	0.00	0.00	-0.01	-0.01	1.00	-0.08	0.07	0.09	0.04
Industry concentration index	-0.05	0.02	0.04	-0.02	-0.02	-0.01	0.03	0.01	-0.02	0.00	0.02	0.02	-0.08	1.00	0.02	-0.04	0.04
Reliance on public information	-0.03	0.02	0.00	0.03	-0.01	0.00	-0.02	-0.04	0.00	0.00	0.01	0.03	0.07	0.02	1.00	-0.03	0.03
Return gap	-0.04	0.13	0.11	0.03	-0.01	0.04	0.14	-0.03	0.18	0.12	0.04	-0.02	0.09	-0.04	-0.03	1.00	-0.04
Active share	-0.09	0.05	-0.06	0.21	-0.10	0.00	-0.20	-0.04	0.01	0.07	0.07	0.10	0.04	0.04	0.03	-0.04	1.00

Figure 6-1 Aggregate Flow-Induced Trade and the Market Index

This figure shows aggregate flow-induced trade (FIT), aggregate expected flow-induced trade (EFIT) and the HS300 market index from 2007-2016. FIT is constructed based on aggregate flow-induced trade across funds. Expected FIT is constructed by replacing actual flow with expected fund flows in FIT calculations. I take average FIT across all sample funds and plot them with the HS300 index.

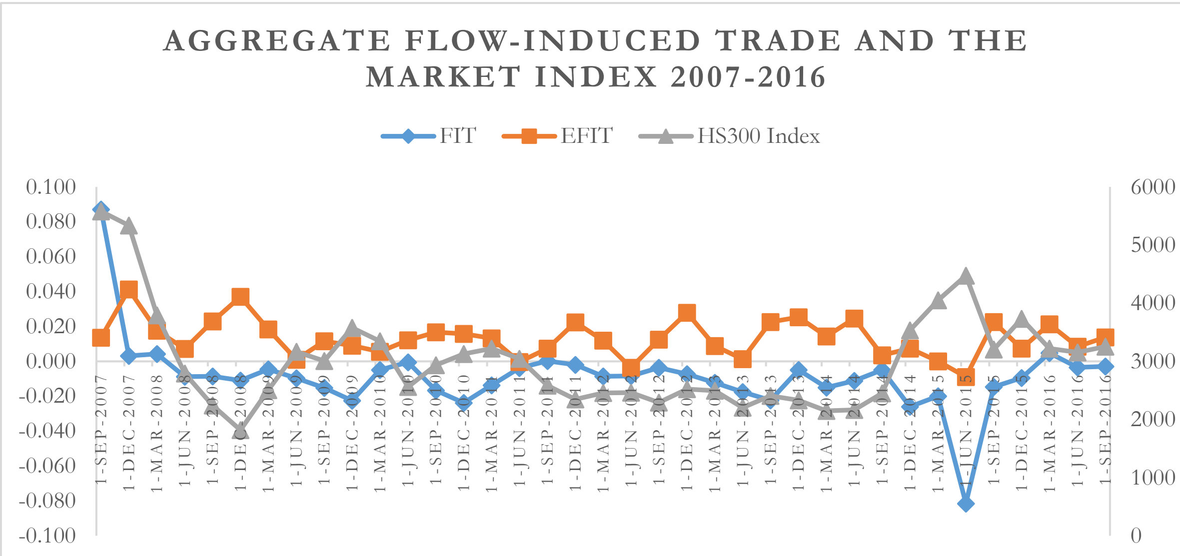


Table 6-1 presents summary statistics for my sample. I report flow-induced trade, anomaly scores, fund characteristics, fund performance and active skills respectively. Average flow-induced trade is -0.013 with a standard deviation of 0.042. Average expected flow-induced trade is 0.012 with a standard deviation of 0.015. For portfolio anomaly score, on average, the top three anomalies invested by the sample funds are return on assets (average 6.985), momentum (average 6.535) and asset growth (average 6.51). The funds have a mean and median of total assets of 3046.75 million yuan and 1648.91 million yuan respectively. The sample funds have an average positive four-factor alpha of 0.53%. In Figure 6-1, I find that when the market was about to reach its top in 2015, fund managers on the aggregate level tended to sell their position with a negative FIT, which is relatively smart, and a similar pattern can also be observed at the end of 2009. It indicates that some fund managers have the ability to trade with good market timing under fund flows.

6.5 Empirical Results

This section presents empirical results. I discuss the construction of flow-induced trade (FIT) in Section 6.5.1, examine the impact of FIT on stock returns in Section 6.5.2 and investigate the relation between FIT and stock return anomalies in Section 6.5.3. Next, I study the impact of FIT on fund performance in Section 6.5.4 and check the robustness of the results in Section 6.5.5.

6.5.1 Construction of Flow-Induced Trade (FIT)

How do fund managers respond to capital flows? Intuitively, fund managers can reinvest capital inflows into their existing holdings or liquidate their holdings to satisfy redemption requirements. To determine how fund managers' trades are influenced by capital flows, firstly, I examine the aggregate effect by regressing changes in holdings on fund flows following Lou (2012). The purpose of this approach is to obtain the partial scaling factors or the coefficients of flows, which will be utilized in the construction of flow-induced trade. The whole mutual fund industry can be viewed as one huge fund. Also, in actual financial markets, the investment philosophies of managers may vary; they are likely to consider common risk factors such as size risk, value risk and momentum risk (Fama and French, 1993; Carhart, 1997) in their trades. I take the ordinary least squares (OLS) regression approach in calculating the PSF (partial scaling factors) of flows and take account of control variables.[32]

$$Trade_{i,j,t} = \beta_0 + \beta_1 * flow_{i,t} + \gamma_2 * SIZE_{j.t} + \gamma_3 * BM_{j,t} + \gamma_4 * MOM_{j,t} + \varepsilon_{i,t}$$

(Eq. 6-2)

$$Trade_{i,j,t} = \frac{shares_{i,j,t}}{shares_{i,j,t-1}} - 1$$

(Eq. 6-3)

Table 6-2 Flow-Induced Trade

This table reports regression results relating to changes in stock holdings by funds resulting from fund flows. The dependent variable is the change in shares held by fund *i* in stock *j* from quarter *t*-1 to *t*. The primary independent variable is fund flows. Control variables include log of stock market capitalization, book-to-market ratio and the Carhart momentum factor measured by prior one-year cumulative returns. The coefficients are estimated using quarter fixed effects regressions with the standard errors clustered at the fund level. Coefficients that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

	The inflow sample			The outflow sample		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Fund flows	0.783***	0.799***	0.800***	0.891***	0.925***	0.903***
	(7.853)	(7.721)	(7.692)	(3.904)	(3.934)	(3.839)
Size (log)		0.027	0.032		-0.001	0.001
		(0.802)	(0.932)		(-0.063)	(0.054)
Book-to-market		-0.001	-0.001		-0.001*	-0.001
		(-0.559)	(-0.558)		(-1.943)	(-1.537)
Momentum			-0.004			0.115***
			(-0.070)			(3.915)
Intercept	1.052***	0.436	0.346	1.573***	1.425**	1.288**
	(3.371)	(0.517)	(0.404)	(3.891)	(2.393)	(2.213)
Cluster fund effects	Yes	Yes	Yes	Yes	Yes	Yes
Fix quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106,132	99,063	97,905	323,424	303,650	300,387
R-squared	0.0180	0.0186	0.0190	0.0018	0.0016	0.0018
Adj. R-squared	0.0175	0.0181	0.0184	0.0017	0.0015	0.0016

[32] Jiang and Verardo (2018) investigate the impact of fund herding on fund trades. Using a similar specification, I also control for size, value and momentum risk.

Table 6-2 presents the results. It shows that the flow sensitivity is asymmetrical for both the inflow sample and the outflow sample. Managers are generally more risk-averse in relation to capital outflows since higher outflows or redemptions induce more trades by fund managers. The dependent variable is $Trade_{i,j,t}$, measured as the rate of change of fund *i* on stock shares of stock *j* from quarter *t*-1 to quarter *t*. The main independent variable is fund flow, measured as the rate of change on fund size from quarter *t*-1 to quarter *t*. Regarding the samples, 1% of inflow leads to 0.783% (t=7.853) to 0.8% (t=7692) of reinvestments in their holdings, while 1% of outflow induces 0.891% (t=3.904) to 0.903% (t=3.839) of stock withdrawals. The coefficients of fund flows in all columns are significant at the 1% level. Column 1 and Column 4 directly decompose the trade of fund managers into flow-driven components and residual components. As fund managers might have more motivations rather than size, value and momentum in their trades, Column 1 and Column 4 provide a simple way to separate flow-driven trades and other information-driven trades. Also, Lou (2012) finds that the return predictability of FIT is not sensitive to the partial scaling factors used in its construction. I take the coefficients in the regressions of Column 1 and Column 4 as partial scaling factors (PSF) to construct the FIT in the next section.

I examine the impact of funds experiencing capital inflows or outflows on individual stocks. I follow the method of Lou (2012) to construct flow-induced trading (FIT) as:

$$FIT_{j,t} = \frac{\sum_i share_{i,j,t-1} * flow_{i,t} * PSF_{I,t-1}}{\sum_i share_{i,j,t-1}}$$

(Eq. 6-4)

Where $flow_{i,t}$ is the quarterly growth of total net assets that is net of returns from capital gains, $share_{i,j,t-1}$ is the number of shares held by fund *i* of stock *j*. PSF is the partial scaling factor, which captures the impact of capital flows on fund managers' trade at the aggregate level. For individual stocks, more explicitly, FIT may be interpreted as the share-weighted average of trade, which is motived by fund flows. Then, I construct portfolios by sorting stocks based on FIT at the end of each quarter and observe the returns of long-short stock portfolios.

6.5.2 FIT and Stock Returns

Table 6-3 Hedge Stock Portfolios Sorted by Flow-Induced Trade

This table reports returns for stock portfolios ranked by flow-induced trading (FIT). The portfolios are rebalanced every quarter and held for three years. At the end of each quarter, stocks are sorted into ten deciles based on flow-induced trade. Equal-weighted and value-weighted monthly portfolio returns of the top decile with the highest FIT, the bottom decile with the lowest FIT, and the spread between the top decile and the bottom decile are reported. I follow Jegadeesh and Titman (1993)'s method to take equal-weighted average return across portfolios formed in different quarters to deal with overlapping portfolios in each month. Monthly returns are adjusted with the risk-free rate, the CAPM, the Fama-French model (FF3), the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5). All *t*-statistics are calculated using the Newey-West corrections with 12 lags. Returns of spread portfolios that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Panel A: Equal-weighted

	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles	Formation quarter					12-month				
Top	2.75%	1.72%	1.00%	1.10%	0.76%	2.64%	1.34%	0.62%	0.79%	0.47%
	(2.37)	(4.76)	(4.35)	(4.49)	(3.12)	(2.22)	(3.83)	(2.29)	(2.69)	(1.59)
Bottom	1.98%	0.99%	0.34%	0.42%	0.21%	2.50%	1.20%	0.45%	0.54%	0.32%
	(1.73)	(2.8)	(1.07)	(1.3)	(0.61)	(2.09)	(3.31)	(1.58)	(1.6)	(1.05)
Top-Bottom	0.77%	0.72%	0.65%	0.68%	0.55%	0.14%	0.14%	0.18%	0.26%	0.15%
	(3.75)***	(3.41)***	(3.34)***	(3.09)***	(3.12)***	(1.6)	(1.44)	(1.58)	(1.93)*	(1.38)

Table 6-3 (continued)

FIT deciles	24-month					36-month				
Top	2.14%	1.16%	0.34%	0.48%	0.21%	1.35%	1.01%	0.04%	0.13%	-0.18%
	(1.84)	(3.23)	(1.9)	(2.17)	(0.94)	(1.35)	(2.67)	(0.38)	(1.11)	(-1.34)
Bottom	2.05%	1.09%	0.23%	0.27%	0.11%	1.35%	1.02%	0.01%	0.02%	-0.20%
	(1.77)	(3.11)	(1.24)	(1.25)	(0.47)	(1.38)	(2.8)	(0.12)	(0.14)	(-1.67)
Top-Bottom	0.09%	0.07%	0.11%	0.20%	0.11%	0.00%	0.00%	0.03%	0.11%	0.02%
	(1.17)	(1.01)	(1.31)	(2.19)**	(1.16)	(0)	(-0.08)	(0.6)	(1.92)*	(0.33)

Panel B: Value-weighted

	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles	Formation quarter					12-month				
Top	3.39%	2.32%	1.87%	1.97%	1.73%	3.18%	1.84%	1.47%	1.60%	1.53%
	(2.82)	(7.44)	(7.34)	(6.67)	(6.88)	(2.57)	(5.81)	(5.39)	(5.18)	(4.7)
Bottom	2.64%	1.60%	1.17%	1.24%	1.25%	2.92%	1.62%	1.18%	1.25%	1.22%
	(2.06)	(4.34)	(3.28)	(3.36)	(3.06)	(2.41)	(5.17)	(4.7)	(4.41)	(4.36)
Top-Bottom	0.75%	0.71%	0.71%	0.73%	0.48%	0.26%	0.22%	0.29%	0.35%	0.31%
	(2.16)**	(2.02)**	(1.97)*	(1.97)*	(1.44)	(1.78)*	(1.64)	(2.55)**	(2.7)***	(2.11)**

FIT deciles	24-month					36-month				
Top	2.69%	1.67%	1.27%	1.37%	1.30%	1.75%	1.40%	0.95%	0.98%	0.88%
	(2.13)	(5.08)	(4.69)	(4.39)	(4.02)	(1.77)	(4.81)	(5.38)	(5.86)	(4.8)
Bottom	2.59%	1.61%	1.09%	1.15%	1.09%	1.87%	1.53%	0.92%	0.93%	0.84%
	(2.16)	(5.39)	(4.88)	(4.44)	(4.28)	(1.9)	(5.15)	(6.14)	(6.15)	(6.09)
Top-Bottom	0.10%	0.06%	0.18%	0.22%	0.22%	-0.12%	-0.14%	0.03%	0.05%	0.04%
	(0.65)	(0.45)	(1.72)*	(2.1)**	(1.72)*	(-1.26)	(-1.37)	(0.37)	(0.69)	(0.54)

Figure 6-2 Cumulative Returns of the Long-Short Portfolio Sorted by FIT

This figure shows cumulative returns for the long-short stock portfolio sorted by flow-induced trade (FIT). The portfolio is rebalanced quarterly and are held for five-years (60 months). The portfolio consists of a long position in the top decile and a short position in the bottom decile based on FIT. The equal-weighted and value-weighted cumulative returns are reported respectively.

Figure 6-2 (continued)

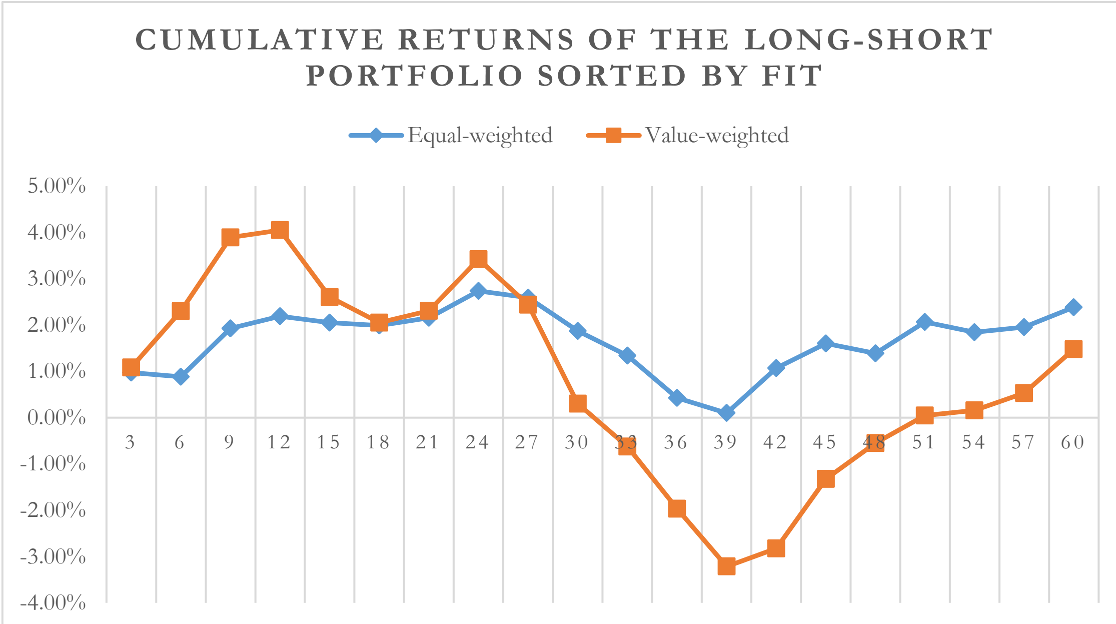


Table 6-3 presents returns for equally-weighted and value-weighted stock portfolios sorted by FIT. The returns are adjusted by the risk-free rate, the CAPM, the Fama-French three-factor model, the Fama-French-Carhart model and the Fama-French five-factor model. In the equally-weighted case, in the formation quarter, the four-factor alphas of the portfolio are 1.10% (t=4.49) in the top decile, 0.42% (t=1.3) in the bottom decile and 0.68% (t=3.09) in the long-short decile. The alpha of the long-short spread is positive and significant at the 1% level. Moreover, the alphas of the hedge portfolio are also positive and significant after formation. They offer a monthly four-factor model alpha of 0.26% (t=1.93) at the 12-month horizon, a monthly four-factor alpha of 0.2% (t=2.19) at the 24-month horizon and a monthly four-factor alpha of 0.11% (t=1.92) at the 36-month horizon. For the value-weighted results, in the formation quarter, the four-factor alphas of the portfolios are: 1.97% (t=6.67) in the top decile, 1.24% (t=3.36) in the bottom decile, and 0.73% (t=1.97) in the long-short decile. The alpha of the long-short spread is positive and significant at the 5% level. Notably, the alphas of long-short spreads remain positive and significant using the four-factor model from its formation to two years. At the 12-month horizon, the long-short portfolio offers a monthly four-factor alpha of 0.35% (t=2.7) or an annualized four-factor alpha of 4.2% (0.35% times 12). In addition, at the 24-month horizon, the long-short portfolio offers a monthly four-factor alpha of 0.22% (t=2.1) or an annualized four-factor alpha of 2.64% (0.22% times 12). In the calculation of *t*-statistics, standard deviations are corrected with Newey-West method with 12 lags following.[33] The results confirm that flow-induced trade does have predictability on stock returns, which is consistent with the US evidence from Lou (2012).

Then, in Figure 6-2, I plot the cumulative excess return patterns of long-short portfolios, which are formed and held for 60 months. For the equal-weighted portfolio, there is a little reversal within the 24-month horizon, and the curve of cumulative return is above zero. The cumulative return of the long-short portfolio increases from 0.89% in the 6^{th} month to its top 2.74% in the 24^{th} month. Then, it drops to its bottom 0.10% in the 39^{th} month. It bounces back and keeps increasing to reach 2.38% in the 60^{th} month. For the value-weighted portfolio, the results also show a little reversal pattern in the first 24 months. The cumulative return of the long-short portfolio keeps increasing from 1.08% in the third month to 4.05% in the twelfth months. Then, it drops to 0.30% in the 30^{th} month which is close to zero. It reaches its lowest value of -3.22% in the 39^{th} month. Finally, it bounces back, turns positive to 0.04% in the 51^{st} month and reaches

[33] Following the method of Greene (2002), optimal lag is determined as the smallest integer that is equal to the 1/4 power of the number of observations. Referring to Greene's approach, I utilize monthly data for risk-adjusted regressions and take 12 lags in the Newey-West corrections. The main results are not sensitive to the length of lags.

the highest value of 1.48% at the 60th month. The findings further confirm the return predictability of flow-induced trade in long horizons.

6.5.3 FIT and Stock Return Anomalies

To investigate the relationship between flow-induced trade and stock return anomalies, first, I examine whether anomaly returns exist in China. Then, I study whether fund managers can exploit anomalies in the right direction. Finally, I study the sources of these smart trades with subsamples based on active skills and fund characteristics.

6.5.3.1 Anomaly Returns

In this section, I explore the long-short returns of nine asset-pricing anomalies from Stambaugh, Yu and Yuan (2012). These anomalies include total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh and Zhang 2004), gross profitability (Novy-Marx, 2013), asset growth (Cooper, Gulen and Schill, 2008), return on assets (Chen, Novy-Marx and Zhang, 2011), investment-to-assets (Titman, Wei and Xie, 2004), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), composite equity issues (Daniel and Titman, 2006) and momentum (Jegadeesh and Titman, 1993). I construct long-short portfolios by ranking the stocks into ten deciles based on the most recently available value for each anomaly at the end of each month.

I then compute the return spread by longing the top decile (decile 10) and shorting the bottom decile (decile 1). I follow Jegadeesh and Titman's (1993) method to buy and hold stocks for 3-36 months after portfolio formation. I calculate equal-weighted and value-weighted returns for the long-short portfolio over each horizon, then I adjust returns with the risk-free rate, the Fama-French three-factor model, the Fama-French-Carhart model, the Fama-French five-factor model and the Q-factor model. I construct each individual anomaly first. Then, for combinations of anomalies, I take average ranks based on individual anomalies. Following Akbas et al. (2015), first, I define asset growth, investment-to-assets, net operating assets and composite equity issues as investment anomaly. Second, the three anomalies documented by literature prior to 1997 comprise net stock issues (1991), momentum (1993) and total accruals (1996). Third, the six anomalies from 1997 forward comprise net operating assets (2004), investment-to-assets (2004), return on assets (2006), composite equity issues (2006), asset growth (2008) and gross profitability premium (2010).

Table 6-4 Hedge Returns of the Nine Asset-Pricing Anomalies Studied by Stambaugh, Yu and Yuan (2012)

The table reports the risk-adjusted returns of hedge stock portfolios based on the stock return anomalies and their combinations from Stambaugh, Yu, Yuan (2012). At the end of each month, stocks are sorted by each anomaly into ten deciles. Then, I take long positions in the top decile and take short positions in the bottom decile to construct long-short portfolios. Equal-weighted and value-weighted monthly returns of the long-short portfolios are adjusted with the risk-free rate, the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart model (FF4), the Fama-French five-factor model (FF5) and the Q-factor model (QF) from Hou, Xue and Zhang (2014). The portfolios are formed and held for 3 to 36 months. Portfolio returns are computed with the method from Jegadeesh and Titman (1993), which takes equal-weighted average returns across portfolios formed in different months to deal with portfolio overlaps. Panel A reports stock characteristics of the long side and the short side; Panel B reports the returns of spread portfolios. All *t*-statistics are calculated using Newey-West corrections with 12 lags. Returns of spread portfolios that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Panel A:

	Stocks in the long leg	Stocks in the short leg
Total accruals	High accruals	Low accruals
Net operating assets	High net operate the asset	Low net operate the asset
Gross profitability	High gross profitability	Low gross profitability
Asset growth	High asset growth	Low asset growth
Return on assets	High return on assets	Low return on assets
Investment-to-assets	High investment-to-assets	Low investment-to-assets
Net stock issues	High net stock issues	Low net stock issues
Composite stock issues	High composite stock issues	Low composite stock issues
Momentum	High momentum	Low momentum

Table 6-4 (continued)

Panel B:

Anomalies	Composite anomalies					Individual anomalies								
	Overall mispricing metric	Non-investment anomalies	Investment anomalies	Three anomalies documented prior to 1997	Six anomalies from 1997 forward	Total accruals	Net operating assets	Gross profitability	Asset growth	Return on assets	Investment -to-assets	Net stock issues	Composite equity issues	Momentum
	3-month					3-month								
Equal-weighted														
Excess return	1.467%	1.704%	0.385%	1.222%	1.066%	0.385%	0.036%	0.628%	0.653%	1.941%	0.107%	2.719%	0.059%	0.073%
	(4.81)***	(5.55)***	(2.07)**	(4.07)***	(3.59)***	(1.93)*	(0.17)	(2.71)***	(4.45)***	(4.3)***	(0.85)	(6.82)***	(0.46)	(0.23)
CAPM alpha	1.455%	1.692%	0.388%	1.138%	1.110%	0.342%	0.061%	0.661%	0.659%	2.014%	0.110%	2.347%	0.033%	0.082%
	(4.85)***	(5.47)***	(2.14)**	(3.97)***	(3.93)***	(1.91)*	(0.32)	(3.14)***	(4.41)***	(4.62)***	(0.87)	(6)***	(0.28)	(0.25)
FF3 alpha	1.788%	2.035%	0.464%	1.218%	1.427%	0.321%	0.112%	0.865%	0.863%	2.546%	0.202%	2.148%	-0.086%	0.602%
	(5.93)***	(6.62)***	(2.5)**	(3.88)***	(5.47)***	(2.23)**	(0.58)	(4.18)***	(5.83)***	(7.24)***	(1.48)	(5.24)***	(-0.68)	(1.92)*
FF4 alpha	1.813%	2.062%	0.488%	1.238%	1.475%	0.318%	0.137%	0.847%	0.874%	2.581%	0.210%	2.159%	-0.090%	0.661%
	(7.99)***	(8.25)***	(3.04)***	(5.41)***	(6.88)***	(2.28)**	(0.78)	(4.96)***	(5.95)***	(7.83)***	(1.76)*	(5.28)***	(-0.71)	(3.52)***
FF5 alpha	1.366%	1.583%	0.288%	0.857%	1.132%	0.314%	-0.036%	0.722%	0.724%	2.119%	0.149%	2.008%	-0.063%	0.448%
	(4.92)***	(5.26)***	(1.89)*	(2.39)**	(5.67)***	(2.27)**	(-0.22)	(3.9)***	(6.14)***	(8.26)***	(1.36)	(4.56)***	(-0.52)	(1.62)
QF alpha	1.542%	1.795%	0.342%	1.022%	1.262%	0.154%	-0.062%	0.798%	0.768%	2.368%	0.170%	2.337%	-0.063%	0.162%
	(5.83)***	(6.05)***	(2.08)**	(3.12)***	(5.95)***	(0.86)	(-0.28)	(3.95)***	(6.69)***	(9.55)***	(1.58)	(6.07)***	(-0.54)	(0.46)
Value-weighted														
Excess return	1.929%	2.383%	0.076%	2.148%	0.875%	0.961%	-0.212%	0.735%	0.632%	1.472%	-0.148%	3.013%	0.174%	0.657%
	(4.64)***	(6.33)***	(0.22)	(5.44)***	(2.03)**	(2.72)***	(-0.57)	(2.78)***	(2.3)**	(2.68)***	(-0.82)	(6.31)***	(0.79)	(1.63)
CAPM alpha	1.919%	2.325%	0.104%	2.034%	0.889%	0.894%	-0.165%	0.698%	0.613%	1.545%	-0.151%	2.776%	0.164%	0.672%
	(4.72)***	(6.22)***	(0.34)	(5.62)***	(2.15)**	(2.75)***	(-0.53)	(2.71)***	(2.31)**	(2.96)***	(-0.84)	(5.91)***	(0.83)	(1.67)*

Table 6-4 (continued)

FF3 alpha	2.383%	2.627%	0.282%	2.051%	1.394%	0.904%	-0.222%	0.885%	0.940%	2.219%	-0.018%	2.734%	0.089%	1.167%
	(5.95)***	(6.75)***	(0.89)	(4.99)***	(3.64)***	(3.33)***	(-0.7)	(3.26)***	(3.77)***	(6.48)***	(-0.1)	(5.06)***	(0.53)	(3)***
FF4 alpha	2.412%	2.656%	0.316%	2.072%	1.455%	0.902%	-0.186%	0.862%	0.950%	2.252%	-0.010%	2.728%	0.084%	1.231%
	(8.38)***	(8.9)***	(1.29)	(6.38)***	(5.49)***	(3.33)***	(-0.6)	(3.37)***	(4.22)***	(8.44)***	(-0.06)	(5.03)***	(0.52)	(3.91)***
FF5 alpha	1.902%	2.209%	-0.023%	1.712%	1.002%	0.858%	-0.454%	0.801%	0.735%	1.796%	-0.006%	2.675%	0.019%	1.041%
	(5.26)***	(5.91)***	(-0.08)	(3.88)***	(3.23)***	(3.27)***	(-1.46)	(3.1)***	(2.91)***	(6.5)***	(-0.04)	(4.7)***	(0.1)	(2.73)***
QF alpha	1.994%	2.469%	-0.049%	1.827%	0.977%	0.657%	-0.471%	0.745%	0.779%	1.992%	-0.134%	2.961%	0.108%	0.646%
	(5.64)***	(6.99)***	(-0.16)	(4.04)***	(2.7)***	(2.06)**	(-1.34)	(2.21)**	(2.87)***	(6.9)***	(-0.77)	(5.4)***	(0.54)	(1.42)

			6-month							**6-month**				
Equal-weighted														
Excess return	1.052%	1.192%	0.345%	0.950%	0.793%	0.353%	-0.006%	0.416%	0.590%	1.301%	0.096%	2.341%	-0.010%	-0.182%
	(3.44)***	(3.82)***	(1.86)*	(3.46)***	(2.53)**	(1.73)*	(-0.02)	(1.66)	(3.97)***	(2.91)***	(0.8)	(5.97)***	(-0.08)	(-0.57)
CAPM alpha	1.039%	1.184%	0.347%	0.866%	0.833%	0.304%	0.022%	0.460%	0.597%	1.370%	0.107%	1.985%	-0.038%	-0.177%
	(3.44)***	(3.78)***	(1.93)*	(3.35)***	(2.85)***	(1.65)	(0.11)	(2.04)**	(3.96)***	(3.22)***	(0.91)	(5.04)***	(-0.37)	(-0.56)
FF3 alpha	1.366%	1.522%	0.417%	0.951%	1.155%	0.293%	0.070%	0.634%	0.810%	1.904%	0.204%	1.782%	-0.187%	0.398%
	(4.65)***	(4.94)***	(2.27)**	(3.3)***	(4.44)***	(2.1)**	(0.35)	(3.1)***	(6.14)***	(5.87)***	(1.75)*	(4.61)***	(-2.05)**	(1.32)
FF4 alpha	1.405%	1.562%	0.439%	0.981%	1.195%	0.288%	0.093%	0.648%	0.818%	1.928%	0.210%	1.799%	-0.192%	0.450%
	(7.03)***	(6.91)***	(3.13)***	(4.88)***	(6.36)***	(2.16)**	(0.5)	(3.82)***	(6.52)***	(6.91)***	(2.31)**	(4.66)***	(-1.98)*	(2.3)**
FF5 alpha	0.991%	1.129%	0.251%	0.645%	0.867%	0.302%	-0.103%	0.498%	0.670%	1.462%	0.127%	1.646%	-0.123%	0.263%
	(3.67)***	(3.75)***	(1.79)*	(1.97)*	(4.29)***	(2.29)**	(-0.62)	(2.62)**	(6.47)***	(6.41)***	(1.61)	(3.95)***	(-1.42)	(1.01)
QF alpha	1.136%	1.290%	0.310%	0.752%	0.995%	0.133%	-0.113%	0.588%	0.719%	1.734%	0.189%	1.987%	-0.094%	-0.116%
	(4.16)***	(4.26)***	(1.77)*	(2.46)**	(4.55)***	(0.73)	(-0.48)	(2.75)**	(7.62)***	(7.57)***	(2.09)**	(5.3)**	(-1.02)	(-0.33)

Table 6-4 (continued)

Value-weighted														
Excess return	1.496%	1.911%	0.097%	1.854%	0.715%	0.949%	-0.227%	0.552%	0.500%	0.927%	-0.155%	2.545%	0.034%	0.415%
	(3.69)***	(5.37)***	(0.32)	(4.99)***	(1.66)	(2.72)***	(-0.57)	(2.05)**	(2.07)**	(1.67)*	(-0.9)	(5.93)***	(0.17)	(1.04)
CAPM alpha	1.470%	1.844%	0.106%	1.725%	0.716%	0.875%	-0.183%	0.523%	0.483%	0.999%	-0.153%	2.332%	0.011%	0.412%
	(3.65)***	(5.14)***	(0.38)	(5.28)***	(1.74)*	(2.76)***	(-0.54)	(2.01)**	(1.97)*	(1.92)*	(-0.88)	(5.3)***	(0.06)	(1.05)
FF3 alpha	1.920%	2.132%	0.293%	1.764%	1.211%	0.902%	-0.258%	0.666%	0.847%	1.659%	0.016%	2.312%	-0.116%	0.979%
	(5.1)***	(5.99)***	(0.98)	(4.82)***	(3.11)***	(3.55)***	(-0.73)	(2.56)**	(4.23)***	(4.9)***	(0.1)	(4.55)***	(-0.78)	(2.71)***
FF4 alpha	1.963%	2.174%	0.323%	1.793%	1.263%	0.898%	-0.228%	0.684%	0.855%	1.682%	0.022%	2.311%	-0.121%	1.035%
	(8.26)***	(8.17)***	(1.46)	(6.12)***	(4.73)***	(3.53)***	(-0.68)	(2.78)***	(5.11)***	(6.86)***	(0.18)	(4.52)***	(-0.79)	(3.49)***
FF5 alpha	1.503%	1.776%	0.033%	1.454%	0.840%	0.859%	-0.514%	0.600%	0.637%	1.179%	-0.003%	2.237%	-0.146%	0.860%
	(4.22)***	(5.12)***	(0.13)	(3.63)***	(2.65)**	(3.54)***	(-1.57)	(2.4)**	(2.91)***	(4)***	(-0.03)	(4.13)***	(-1.07)	(2.4)**
QF alpha	1.561%	1.965%	-0.024%	1.520%	0.781%	0.656%	-0.533%	0.542%	0.636%	1.439%	-0.099%	2.513%	0.004%	0.352%
	(4.18)***	(5.61)***	(-0.08)	(3.59)***	(2.15)**	(2.09)**	(-1.44)	(1.62)	(2.73)**	(4.9)***	(-0.65)	(5.13)***	(0.02)	(0.78)
	12-month							**12-month**						
Equal-weighted														
Excess return	0.544%	0.598%	0.216%	0.493%	0.396%	0.251%	-0.080%	0.232%	0.390%	0.591%	0.103%	1.655%	-0.026%	-0.488%
	(1.74)*	(1.93)*	(1.22)	(2.37)**	(1.22)	(1.2)	(-0.32)	(0.87)	(2.91)***	(1.27)	(1.02)	(4.59)***	(-0.23)	(-1.52)
CAPM alpha	0.549%	0.602%	0.230%	0.421%	0.451%	0.198%	-0.042%	0.281%	0.395%	0.679%	0.120%	1.329%	-0.042%	-0.476%
	(1.83)*	(2)**	(1.39)	(2.07)**	(1.52)	(1.05)	(-0.2)	(1.18)	(2.92)***	(1.57)	(1.23)	(3.62)***	(-0.43)	(-1.55)
FF3 alpha	0.905%	0.970%	0.314%	0.530%	0.803%	0.189%	0.001%	0.473%	0.611%	1.228%	0.222%	1.127%	-0.181%	0.177%
	(3.28)***	(3.49)***	(1.91)*	(2.46)**	(3.16)***	(1.31)	(0)	(2.21)**	(5.58)***	(3.91)***	(2.61)**	(3.37)***	(-2.03)**	(0.67)
FF4 alpha	0.960%	1.026%	0.349%	0.568%	0.872%	0.179%	0.041%	0.491%	0.630%	1.289%	0.235%	1.150%	-0.185%	0.216%
	(5.18)***	(5.01)***	(3)**	(3.83)***	(4.79)***	(1.27)	(0.22)	(2.76)***	(6.17)***	(5.07)***	(3.61)***	(3.41)***	(-1.96)*	(1.11)
FF5 alpha	0.560%	0.619%	0.182%	0.271%	0.543%	0.193%	-0.175%	0.329%	0.505%	0.816%	0.162%	1.008%	-0.118%	0.052%
	(2.24)**	(2.29)**	(1.41)	(1.07)	(2.68)***	(1.34)	(-0.99)	(1.65)	(6.45)***	(3.64)***	(2.82)***	(2.83)***	(-1.44)	(0.24)
QF alpha	0.663%	0.739%	0.207%	0.311%	0.638%	0.018%	-0.171%	0.438%	0.538%	1.071%	0.175%	1.314%	-0.083%	-0.381%
	(2.6)**	(2.77)***	(1.34)	(1.34)	(2.88)***	(0.09)	(-0.71)	(1.94)*	(8.3)***	(4.84)***	(2.85)***	(4.09)***	(-0.95)	(-1.16)

Table 6-4 (continued)

Value-weighted														
Excess return	0.926%	1.254%	0.071%	1.319%	0.479%	0.871%	-0.301%	0.428%	0.393%	0.306%	-0.138%	1.780%	-0.034%	0.045%
	(2.49)**	(3.75)***	(0.25)	(5.12)***	(1.17)	(2.63)**	(-0.71)	(1.56)	(2.03)**	(0.54)	(-0.9)	(4.77)***	(-0.26)	(0.12)
CAPM alpha	0.904%	1.201%	0.088%	1.194%	0.470%	0.794%	-0.258%	0.399%	0.363%	0.389%	-0.129%	1.596%	-0.041%	0.027%
	(2.43)**	(3.5)***	(0.33)	(5.12)***	(1.2)	(2.67)***	(-0.72)	(1.5)	(1.81)*	(0.74)	(-0.83)	(4.12)***	(-0.35)	(0.07)
FF3 alpha	1.353%	1.515%	0.266%	1.264%	0.986%	0.833%	-0.339%	0.549%	0.699%	1.054%	0.021%	1.553%	-0.193%	0.704%
	(3.97)***	(4.62)***	(0.98)	(4.83)***	(2.68)***	(3.46)***	(-0.9)	(2.05)**	(4.88)***	(3.03)***	(0.15)	(3.46)***	(-1.83)	(2.47)**
FF4 alpha	1.412%	1.573%	0.312%	1.303%	1.077%	0.827%	-0.284%	0.571%	0.714%	1.110%	0.030%	1.557%	-0.196%	0.747%
	(6.41)***	(6.07)***	(1.48)	(6.61)***	(4.03)***	(3.37)***	(-0.8)	(2.33)**	(5.82)***	(4.58)***	(0.24)	(3.44)***	(-1.8)	(3.02)***
FF5 alpha	0.987%	1.176%	0.104%	1.008%	0.690%	0.773%	-0.590%	0.453%	0.552%	0.599%	0.019%	1.476%	-0.217%	0.577%
	(3.1)***	(3.57)***	(0.44)	(3.39)***	(2.32)**	(3.28)***	(-1.65)	(1.76)*	(3.49)***	(1.85)*	(0.16)	(3.01)***	(-2.25)**	(2.42)**
QF alpha	1.005%	1.346%	-0.032%	0.994%	0.560%	0.591%	-0.618%	0.433%	0.562%	0.858%	-0.053%	1.735%	-0.052%	-0.011%
	(3.1)***	(4.46)***	(-0.13)	(3.3)***	(1.65)	(1.93)*	(-1.59)	(1.29)	(3.39)***	(3.07)***	(-0.4)	(4.45)***	(-0.5)	(-0.03)
	24-month					**24-month**								
Equal-weighted														
Excess return	-0.019%	-0.020%	0.020%	0.050%	0.013%	0.287%	-0.235%	0.009%	0.026%	-0.064%	-0.010%	0.796%	-0.022%	-0.717%
	(-0.06)	(-0.07)	(0.12)	(0.25)	(0.04)	(1.45)	(-0.94)	(0.04)	(0.2)	(-0.15)	(-0.11)	(2.53)**	(-0.22)	(-2.41)**
CAPM alpha	-0.005%	-0.001%	0.032%	0.005%	0.060%	0.236%	-0.201%	0.061%	0.030%	0.022%	0.001%	0.501%	-0.036%	-0.696%
	(-0.02)	(-0.01)	(0.2)	(0.03)	(0.21)	(1.38)	(-0.94)	(0.26)	(0.24)	(0.06)	(0.01)	(1.75)*	(-0.42)	(-2.57)**
FF3 alpha	0.381%	0.410%	0.128%	0.143%	0.432%	0.150%	-0.181%	0.267%	0.256%	0.621%	0.124%	0.304%	-0.160%	-0.028%
	(1.47)	(1.66)	(0.75)	(0.78)	(1.71)	(1)	(-0.91)	(1.21)	(2.43)**	(2.06)**	(1.49)	(1.18)	(-1.99)*	(-0.13)
FF4 alpha	0.469%	0.491%	0.186%	0.192%	0.540%	0.130%	-0.115%	0.302%	0.295%	0.749%	0.152%	0.326%	-0.163%	-0.003%
	(2.43)**	(2.64)**	(1.42)	(1.38)	(2.84)***	(0.87)	(-0.66)	(1.63)	(3.35)***	(3.24)***	(2.34)**	(1.26)	(-1.92)*	(-0.02)
FF5 alpha	0.173%	0.200%	0.019%	-0.017%	0.212%	0.155%	-0.329%	0.114%	0.216%	0.340%	0.094%	0.249%	-0.114%	-0.143%
	(0.77)	(0.89)	(0.14)	(-0.08)	(1.05)	(0.98)	(-1.71)*	(0.57)	(2.94)***	(1.48)	(1.62)	(0.88)	(-1.43)	(-0.87)
QF alpha	0.189%	0.233%	-0.031%	-0.087%	0.225%	0.037%	-0.351%	0.220%	0.236%	0.526%	0.103%	0.473%	-0.087%	-0.566%
	(0.82)	(1.04)	(-0.2)	(-0.44)	(0.98)	(0.2)	(-1.4)	(0.93)	(3.58)***	(2.47)**	(1.95)*	(1.83)*	(-1.1)	(-2.07)**

Table 6-4 (continued)

Value-weighted															
Excess return	0.122%	0.388%	-0.109%	0.670%	0.053%	0.966%	-0.596%	0.255%	-0.031%	-0.516%	-0.188%	0.934%	0.054%	-0.484%	
	(0.31)	(1.08)	(-0.42)	(2.54)**	(0.15)	(2.96)***	(-1.42)	(0.98)	(-0.16)	(-0.86)	(-1.13)	(3.05)***	(0.51)	(-1.41)	
CAPM alpha	0.086%	0.355%	-0.124%	0.570%	0.026%	0.886%	-0.563%	0.218%	-0.051%	-0.456%	-0.185%	0.780%	0.044%	-0.491%	
	(0.21)	(0.99)	(-0.47)	(2.31)**	(0.07)	(3.21)***	(-1.53)	(0.87)	(-0.26)	(-0.78)	(-1.05)	(2.66)***	(0.47)	(-1.49)	
FF3 alpha	0.572%	0.783%	0.001%	0.672%	0.537%	0.841%	-0.737%	0.392%	0.253%	0.283%	-0.045%	0.745%	-0.157%	0.223%	
	(1.42)	(2.23)**	(0)	(2.5)**	(1.53)	(3.3)***	(-2.04)**	(1.5)	(1.48)	(0.61)	(-0.28)	(2.17)**	(-1.27)	(0.89)	
FF4 alpha	0.675%	0.871%	0.079%	0.731%	0.676%	0.834%	-0.652%	0.436%	0.280%	0.406%	-0.028%	0.750%	-0.160%	0.253%	
	(2.38)**	(3.31)***	(0.35)	(3.58)***	(2.52)**	(3.22)***	(-1.96)*	(1.83)*	(1.83)*	(1.19)	(-0.18)	(2.19)**	(-1.3)	(1.14)	
FF5 alpha	0.321%	0.548%	-0.122%	0.496%	0.309%	0.813%	-0.925%	0.276%	0.232%	-0.073%	-0.021%	0.742%	-0.192%	0.100%	
	(0.85)	(1.54)	(-0.52)	(1.8)*	(1.19)	(3.31)***	(-2.59)**	(1.13)	(1.67)*	(-0.16)	(-0.15)	(1.94)*	(-1.31)	(0.49)	
QF alpha	0.357%	0.641%	-0.320%	0.394%	0.089%	0.738%	-1.003%	0.226%	0.224%	0.218%	-0.043%	0.871%	0.015%	-0.443%	
	(1.04)	(2.07)**	(-1.18)	(1.48)	(0.25)	(2.63)**	(-2.59)**	(0.63)	(1.47)	(0.62)	(-0.32)	(2.98)***	(0.17)	(-1.31)	
	36-month					**36-month**									
Equal-weighted															
Excess return	-0.227%	-0.195%	-0.092%	0.002%	-0.213%	0.413%	-0.304%	-0.159%	-0.114%	-0.368%	-0.035%	0.358%	0.070%	-0.748%	
	(-0.9)	(-0.81)	(-0.64)	(0.01)	(-0.75)	(2.42)**	(-1.27)	(-0.67)	(-1.11)	(-0.91)	(-0.44)	(2.55)**	(0.87)	(-2.78)***	
CAPM alpha	-0.214%	-0.175%	-0.085%	-0.051%	-0.173%	0.348%	-0.267%	-0.112%	-0.114%	-0.286%	-0.030%	0.296%	0.045%	-0.703%	
	(-0.97)	(-0.81)	(-0.64)	(-0.29)	(-0.71)	(2.29)**	(-1.33)	(-0.53)	(-1.16)	(-0.8)	(-0.37)	(2.28)**	(0.66)	(-3.05)***	
FF3 alpha	0.166%	0.236%	-0.001%	0.059%	0.185%	0.222%	-0.247%	0.101%	0.086%	0.294%	0.091%	0.184%	-0.075%	-0.098%	
	(0.85)	(1.28)	(-0.01)	(0.38)	(0.89)	(1.63)	(-1.38)	(0.52)	(1.26)	(1.14)	(1.38)	(1.89)*	(-1.2)	(-0.54)	
FF4 alpha	0.334%	0.389%	0.074%	0.140%	0.327%	0.177%	-0.153%	0.171%	0.132%	0.465%	0.128%	0.197%	-0.077%	-0.073%	
	(1.87)*	(2.42)**	(0.67)	(1.06)	(1.88)*	(1.2)	(-0.96)	(0.96)	(1.97)*	(2.27)**	(2.11)**	(1.95)*	(-1.21)	(-0.45)	
FF5 alpha	0.096%	0.163%	-0.061%	0.006%	0.059%	0.239%	-0.357%	0.004%	0.092%	0.141%	0.080%	0.157%	-0.051%	-0.178%	
	(0.5)	(0.85)	(-0.53)	(0.03)	(0.31)	(1.64)	(-1.9)*	(0.02)	(1.68)*	(0.64)	(1.81)*	(1.43)	(-0.84)	(-1.26)	
QF alpha	0.092%	0.195%	-0.116%	-0.071%	0.052%	0.146%	-0.421%	0.064%	0.114%	0.292%	0.096%	0.291%	0.000%	-0.588%	
	(0.48)	(1)	(-0.97)	(-0.39)	(0.26)	(0.87)	(-1.82)*	(0.28)	(2.18)**	(1.45)	(2.39)**	(2.37)**	(0)	(-2.22)**	

Table 6-4 (continued)

Value-weighted

Excess return	-0.113%	0.186%	-0.232%	0.592%	-0.243%	1.078%	-0.646%	0.075%	-0.166%	-0.787%	-0.129%	0.616%	0.092%	-0.617%
	(-0.33)	(0.53)	(-1)	(2.23)**	(-0.7)	(3.38)***	(-1.6)	(0.3)	(-0.97)	(-1.3)	(-0.9)	(2.77)***	(0.92)	(-1.97)*
CAPM alpha	-0.170%	0.144%	-0.269%	0.471%	-0.292%	0.970%	-0.603%	0.024%	-0.184%	-0.725%	-0.133%	0.534%	0.060%	-0.582%
	(-0.5)	(0.43)	(-1.13)	(1.84)*	(-0.84)	(3.57)***	(-1.76)*	(0.1)	(-1.04)	(-1.24)	(-0.88)	(2.47)**	(0.71)	(-2.05)**
FF3 alpha	0.334%	0.627%	-0.161%	0.575%	0.200%	0.893%	-0.810%	0.188%	0.096%	0.029%	0.014%	0.567%	-0.137%	0.098%
	(1.03)	(2.1)**	(-0.63)	(2.48)**	(0.62)	(3.62)***	(-2.41)**	(0.76)	(0.65)	(0.06)	(0.11)	(2.31)**	(-1.3)	(0.44)
FF4 alpha	0.527%	0.799%	-0.057%	0.673%	0.385%	0.878%	-0.696%	0.278%	0.130%	0.199%	0.032%	0.575%	-0.140%	0.132%
	(1.99)*	(3.09)***	(-0.26)	(3.4)***	(1.42)	(3.43)***	(-2.19)**	(1.2)	(0.99)	(0.54)	(0.24)	(2.33)**	(-1.31)	(0.67)
FF5 alpha	0.273%	0.548%	-0.195%	0.512%	0.115%	0.921%	-0.961%	0.154%	0.148%	-0.162%	0.050%	0.588%	-0.187%	0.008%
	(0.82)	(1.59)	(-0.84)	(1.94)**	(0.44)	(3.83)***	(-2.75)***	(0.62)	(1.17)	(-0.35)	(0.43)	(2.17)**	(-1.41)	(0.04)
QF alpha	0.284%	0.633%	-0.385%	0.429%	-0.100%	0.849%	-1.117%	0.067%	0.144%	0.052%	0.018%	0.596%	0.023%	-0.495%
	(0.93)	(1.99)*	(-1.57)	(1.62)	(-0.29)	(3.09)***	(-3.11)***	(0.18)	(1.21)	(0.13)	(0.16)	(2.86)***	(0.3)	(-1.5)

The mispricing-metrics are of economic and statistical significance. In Table 6-4, in Panel A, I describe stock characteristics on the long and short sides of the hedge stock portfolios. In Panel B, I present monthly long-short return spreads of composite and individual anomalies.

For the overall mispricing metric, it shows positive and significant returns of the spread portfolio from 3-24 months. It offers a value-weighted four-factor alpha of 2.412% (t= 8.38) monthly or 28.944% (t=8.38) annually over a 3-month horizon, and a value-weighted four-factor alpha of 0.675% (t=2.38) monthly or 8.1% (t=2.38) annually over a 24-month horizon. The return spreads of the overall mispricing metric within a 6-month horizon are significant at the 1% level. It suggests the overall mispricing metric is more pronounced in the period near formation.

For individual anomalies, the results show that total accruals, gross profitability, asset growth, return on assets, net stock issues and momentum are consistently positive and significant from 3 months to 12 months. In a 3-month holding period, these six anomalies have been found to have significant positive returns in both equal-weighted and value-weighted portfolios. Total accruals has a five-factor alpha ranging from 0.314% (t=2.27) for an equal-weighted portfolio to 0.858% (t=3.27) for a value-weighted portfolio. Gross profitability has a five-factor alpha ranging from 0.722% (t=3.9) for an equal-weighted portfolio to 0.801% (t=3.1) for a value-weighted portfolio. Asset growth has a five-factor alpha ranging from 0.724% (t=6.14) for an equal-weighted portfolio to 0.735% (t=2.91) for a value-weighted portfolio. Return on assets has a five-factor alpha ranging from 2.119% (t=8.26) for an equal-weighted portfolio to 1.796% (t=6.5) for a value-weighted portfolio. Net stock issues has a five-factor alpha ranging from 2.008% (t=4.56) for an equal-weighted portfolio to 2.675% (t=4.7) for a value-weighted portfolio. Momentum has a four-factor alpha ranging from 0.661% (t=3.52) for an equal-weighted portfolio to 1.231% (t=3.91) for a value-weighted portfolio.

As for composite anomalies, non-investment anomalies, three anomalies documented prior to 1997 and the six anomalies from 1997 forward also show positive and significant returns of the spread portfolios over 3-month to 12-month horizons. Over a 3-month horizon, non-investment anomalies, three anomalies documented prior to 1997 and six anomalies from 1997 forward have positive and significant return spreads for both equal-weighted and value-weighted portfolios, while investment anomalies show a positive return spread for an equal-weighted portfolio. Non-investment anomalies have a five-factor alpha ranging from 1.583% (t=5.26) for an equal-weighted portfolio to 2.209% (t=5.91) for a value-weighted portfolio. Investment anomalies have a four-factor alpha ranging from 0.488% (t=3.04) for an equal-weighted portfolio to 0.316% (t=1.29) for a value-weighted portfolio. The three anomalies documented prior to 1997 have a five-factor alpha ranging from 0.857% (t=2.39) for an equal-weighted portfolio to 1.712% (t=3.88) for a value-weighted portfolio. The six anomalies from 1997 forward have a five-factor alpha ranging from 1.132% (t=5.67) for an equal-weighted portfolio to 1.002% (t=3.23) for a value-weighted portfolio. The results suggest that the anomaly returns studied by Stambaugh, Yu and Yuan (2012) also exist in China. As stock return anomalies provide considerable profits for sophisticated investors, I expect skilled managers may recognize them and tilt their portfolios to trade on them.

6.5.3.2 Are Active Funds Able to Exploit Stock Return Anomalies?

In this section, I examine the relationship between flow-induced trade and stock return anomalies. It allows us to understand if fund managers can tilt their portfolio to undervalued stocks based on the nine anomalies from Stambaugh, Yu and Yuan (2012) when they trade motivated by fund flows.

I rank the stocks universe into ten deciles at the end of each month based on each individual anomaly. Each stock has a decile rank at the end of each month. Then, utilizing fund holding data to identify the stocks and obtain their market value in a fund portfolio, I compute the portfolio-level anomaly rank as the value-weighted average of the decile ranks of each individual anomaly. Furthermore, I compute the rank of each composite anomaly as the average ranks of individual anomalies. Finally, I run regressions of nine individual anomaly ranks and composite anomaly ranks on flow-induced trade. A positive coefficient indicates that fund managers tilt their portfolio to an undervalued stock or sell an overvalued stock measured by a stock return anomaly, which is similar to the long-side or short-side of a long-short hedge strategy based on stock return anomalies in the previous section. In contrast, a negative coefficient implies a reverse trading direction.

Table 6-5 Flow-Induced Trade and Stock Return Anomalies

This table reports the Fama-Macbeth (1973) regressions of anomaly ranks on flow-induced trade. Based on nine anomalies following Stambough, Yu and Yuan (2012), stocks are ranked into ten deciles at the end of each month. I take the value-weighted rank of each anomaly as a portfolio anomaly rank. Individual anomalies include total accruals, net operating assets, gross profitability, asset growth, return on assets, investment-to-assets, net stock issues, composite equity issues and momentum. For a combination of anomalies, I take average rank based on individual anomalies. Following Akbas et al. (2015), I define asset growth, investment-to-assets, net operating assets and composite equity issues as investment anomalies. The three anomalies documented by literature prior to 1997 comprise net stock issues (1991), momentum (1993) and total accruals (1996). The six anomalies from 1997 forward comprise the net operating assets (2004), investment-to-assets (2004), return on assets (2006), composite equity issues (2006), asset growth (2008) and gross profitability (2010). Control variables comprise fund size (log), fund family size (log), the Fama-French-Carhart alpha, fund age (log) and the prior 12-months return volatility. Panel A reports results based on individual anomalies; Panel B reports results based on a combination of anomaly metrics. Standard errors of coefficients are corrected using the Newey-West methods with 12 lags. Coefficients that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Table 6-5 (continued)

Table 6-5 (continued)

Panel A:

Variables	Total accruals	Net operating assets	Gross profitability	Asset growth	Return on assets	Investment-to-assets	Net stock issues	Composite equity issues	Momentum
Flow-induced trade	4.036**	4.888***	-5.612**	-3.127	-3.047	-1.806	0.045	2.094	14.51***
	(2.421)	(3.682)	(-2.346)	(-1.444)	(-1.158)	(-1.115)	(0.016)	(0.788)	(2.905)
Fund size (log)	0.025***	0.008	0.039***	0.034***	0.055***	0.032***	0.002	-0.005	0.044**
	(2.865)	(0.566)	(3.005)	(3.054)	(3.280)	(8.837)	(0.149)	(-0.409)	(2.405)
Family size (log)	-0.029***	0.004	-0.009	-0.025***	-0.028***	-0.013*	-0.004	0.026***	-0.020
	(-2.787)	(0.332)	(-0.569)	(-2.798)	(-3.057)	(-1.723)	(-0.211)	(2.768)	(-0.527)
FF4 alpha	0.730***	-0.287	1.092**	2.665***	1.675*	0.781	-0.546	-0.329	3.639***
	(3.147)	(-0.333)	(2.304)	(3.543)	(1.794)	(1.167)	(-1.110)	(-0.308)	(3.113)
Fund age (log)	-0.063**	-0.027	-0.034	-0.046	-0.050	-0.023	-0.068	0.028	-0.032
	(-2.348)	(-0.709)	(-1.430)	(-1.558)	(-1.385)	(-1.517)	(-1.069)	(1.138)	(-0.408)
Return volatility	1.942	3.948***	-3.165**	-1.156	-3.978	0.027	0.507	-0.840	1.178
	(1.368)	(4.308)	(-2.082)	(-1.085)	(-1.626)	(0.038)	(0.833)	(-1.012)	(0.348)
Intercept	5.940***	4.811***	5.551***	6.513***	6.738***	5.752***	6.103***	5.053***	6.153***
	(28.13)	(11.58)	(19.78)	(18.98)	(19.93)	(23.37)	(15.01)	(15.81)	(5.952)
Observations	10917	10917	10917	10917	10917	10917	10917	10917	10917
R-squared	0.0571	0.0731	0.0628	0.0801	0.0892	0.0564	0.0940	0.0831	0.1336
Adjusted R-	0.0293	0.0456	0.0351	0.0530	0.0622	0.0289	0.0670	0.0565	0.1076

Table 6-5 (continued)

Panel B:

Variables	Overall mispricing metric	Non-investment anomalies	Investment anomalies	Three anomalies documented prior to 1997	Six anomalies from 1997 forward
Flow-induced trade	1.331**	1.986*	0.512	6.197***	-1.101*
	(2.080)	(1.855)	(1.357)	(4.506)	(-1.968)
Fund size (log)	0.026***	0.033***	0.017***	0.024**	0.027***
	(3.688)	(2.981)	(3.434)	(2.187)	(4.119)
Family size (log)	-0.011**	-0.018**	-0.001	-0.018	-0.007***
	(-2.095)	(-2.198)	(-0.789)	(-1.155)	(-3.120)
FF4 alpha	1.046***	1.318**	0.707**	1.274**	0.933***
	(3.061)	(2.463)	(2.322)	(2.395)	(3.587)
Fund age (log)	-0.035***	-0.049**	-0.017***	-0.054**	-0.025***
	(-3.176)	(-2.685)	(-3.946)	(-2.061)	(-4.814)
Return volatility	-0.170	-0.703	0.494*	1.209	-0.861
	(-0.271)	(-0.677)	(1.835)	(0.763)	(-1.356)
Intercept	5.846***	6.097***	5.532***	6.065***	5.736***
	(24.92)	(19.70)	(37.57)	(13.81)	(38.15)
Observations	10917	10917	10917	10917	10917
R-squared	0.0921	0.0964	0.0641	0.1081	0.0790
Adjusted R-	0.0651	0.0694	0.0364	0.0813	0.0516

In Table 6-5 Panel A, it shows that flow-induced trade is positive and significantly associated with total accruals (4.036, t=2.421), net operating assets (4.888, t=3.682) and momentum (14.51, t=2.905), but negative and significantly related to gross profitability (-5.612, t=2.346). For composite anomalies, flow-induced trade is positive and significantly associated with the three anomalies prior to 1997 (6.197, t=4.506), non-investment anomalies (1.986, t=1.855) and the overall mispricing metric (1.331, t=2.08).

The results show that fund managers may have the ability to exploit single anomalies such as total accruals, net operating assets and momentum. In addition, some fund managers may trade on composite signals of combinations of anomalies rather than individual ones. The results further show that fund managers may have the ability to trade on composite signals based on the three anomalies prior to 1997, non-investment anomalies and the overall mispricing metric. Consistent with the literature on active management (Kacoerczyk, Sialm and Zheng, 2005; Kacperczyk and Seru, 2007; Cremers and Petajisto, 2009), it implies that active fund managers may be not dumb as people assume (Akbas et al., 2015). Although gross profitability shows a negative coefficient, indicating that funds may not recognize some individual anomalies, fund managers appear to exploit a wide range of anomalies, including total accruals, net operating assets, momentum, the three anomalies prior to 1997, non-investment anomalies and the overall mispricing metric.

6.5.3.3 Sources of Smart Trade: Active Skills

There is a large body of literature that documents how investors can identify superior performing fund using active investment factors. Pollet and Wilson (2008) find that funds with greater diversification in their holdings tend to outperform other funds with less diversification, and this is more pronounced in small size funds. Kacperczyk, Sialm and Zheng (2005) find that funds that invest more in concentrated industries tend to outperform their peers. Kacperczyk and Seru (2007) find that skilled managers rely less on public information based on analyst recommendations for stocks. Kacperczyk, Sialm and Zheng (2008) document that the return gaps imply hidden benefits of mutual funds, which predict fund performance. I expect funds with superior skills based on active investment factors to tend more towards tilting their portfolio to undervalued stocks measured by composite anomalies, as studied by Akbas et al. (2015).

In this section, I explore whether funds with higher active skills trade more in undervalued stocks based on composite anomaly signals. I split the sample by the median value of each active skill across all funds, then run regressions of composite mispricing ranks on flow-induced trade and control variables.

Table 6-6 Sources of Smart Trading Based on Active Investment Factors: Flow-Induced Trade and Stock Return Anomalies

This table reports the Fama-Macbeth (1973) regressions of composite anomaly ranks on flow-induced trade under different active investment factors. I split the sample based on fund diversification, industry concentration, reliance on public information and return gap. Based on nine anomalies following Stambaugh, Yu and Yuan (2012), stocks are ranked into ten deciles at the end of each month. I take the value-weight rank of each anomaly as its portfolio anomaly rank. Individual anomalies include total accruals, net operating assets, gross profitability, asset growth, return on assets, investment-to-assets, net stock issues, composite equity issues and momentum. For combinations of anomalies, I take average rank based on individual anomalies. Following Akbas et al. (2015), I define asset growth, investment-to-assets, net operating assets and composite equity issues as investment anomalies. The three anomalies documented by the literature prior to 1997 include net stock issues (1991), momentum (1993) and total accruals (1996). The six anomalies from 1997 forward comprise net operating assets (2004), investment-to-assets (2004), return on assets (2006), composite equity issues (2006), asset growth (2008) and gross profitability (2010). Control variables include fund size (log), fund family size (log), the Fama-French-Carhart alpha, fund age (log) and prior 12-months return volatility. Panel A reports the results based on individual anomaly; Panel B reports the results based on the combinations of anomaly metrics. Standard errors of coefficients are corrected using the Newey-West methods with 12 lags. Coefficients that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Panel A:

Variables	Non-investment anomalies	Investment anomalies	Three anomalies documented prior to 1997	Six anomalies from 1997 forward	Overall mispricing metric	Non-investment anomalies	Investment anomalies	Three anomalies documented prior to 1997	Six anomalies from 1997 forward	Overall mispricing metric
	High return gap					Low return gap				
Flow-induced trade	3.645**	1.415*	7.945***	0.008	2.654***	1.852	0.405	6.818***	-1.595	1.209
	(2.410)	(1.985)	(4.483)	(0.016)	(3.060)	(1.177)	(0.619)	(4.614)	(-1.605)	(1.421)
Return gap	-0.078	-0.268**	-0.043	-0.222*	-0.162*	-0.250***	-0.140*	-0.430***	-0.086	-0.201***
	(-0.625)	(-2.139)	(-0.282)	(-1.885)	(-1.749)	(-5.029)	(-1.828)	(-6.482)	(-1.346)	(-4.398)
Fund size (log)	0.042***	0.018**	0.036**	0.029***	0.031***	0.027*	0.012*	0.019	0.021**	0.020*
	(3.933)	(2.216)	(2.598)	(3.741)	(4.088)	(1.823)	(1.911)	(1.549)	(2.122)	(1.940)
Fund family size (log)	-0.045***	0.001	-0.050***	-0.012***	-0.024***	-0.010	0.000	0.000	-0.008	-0.005
	(-5.605)	(0.166)	(-3.039)	(-2.780)	(-4.156)	(-0.852)	(0.046)	(0.024)	(-1.278)	(-0.896)
FF4 alpha	1.162**	0.291	1.547***	0.389	0.775**	1.150*	1.311***	0.888	1.388***	1.221***
	(2.440)	(1.023)	(2.749)	(1.210)	(2.152)	(1.797)	(3.786)	(1.290)	(4.798)	(2.978)

Table 6-6 (continued)

Fund age (log)	-0.067**	0.014	-0.052	-0.020	-0.031	-0.039**	-0.047*	-0.082***	-0.023*	-0.043**
	(-2.104)	(0.654)	(-1.193)	(-1.475)	(-1.485)	(-2.267)	(-1.919)	(-3.106)	(-1.749)	(-2.712)
Return volatility	-0.260	0.601**	1.153	-0.393	0.122	-1.280	-0.242	0.032	-1.244	-0.819
	(-0.312)	(2.444)	(0.804)	(-0.556)	(0.236)	(-1.124)	(-0.435)	(0.019)	(-1.584)	(-0.998)
Intercept	6.456***	5.298***	6.369***	5.728***	5.941***	6.126***	5.770***	6.069***	5.917***	5.968***
	(25.74)	(61.61)	(15.77)	(42.57)	(35.95)	(14.10)	(27.98)	(9.103)	(35.00)	(18.51)
Observations	4190	4190	4190	4190	4190	4168	4168	4168	4168	4168
R-squared	0.1461	0.1212	0.1657	0.126	0.1289	0.1546	0.1454	0.1751	0.1523	0.1671
Adjusted R-squared	0.055	0.0306	0.077	0.0325	0.0334	0.0662	0.0562	0.0881	0.0637	0.0825

Panel B:

	High industry concentration					**Low industry concentration**				
Flow-induced trade	5.179***	1.682*	9.906***	0.484	3.625***	1.440	1.273	6.491***	-1.196	1.366
	(3.195)	(1.976)	(3.301)	(0.576)	(3.674)	(1.124)	(1.223)	(4.878)	(-0.917)	(1.332)
Industry concentration index	0.885	0.630	-0.128	1.222*	0.772	0.046	1.159**	0.908	0.357	0.541
	(1.116)	(1.270)	(-0.175)	(1.899)	(1.465)	(0.060)	(2.476)	(1.161)	(0.708)	(1.123)
Fund size (log)	0.043***	0.020***	0.036***	0.031***	0.033***	0.037***	0.019***	0.028**	0.030***	0.029***
	(4.939)	(2.975)	(4.172)	(3.849)	(4.945)	(3.734)	(3.535)	(2.463)	(4.544)	(3.975)
Fund family size (log)	-0.040***	-0.010	-0.045**	-0.017*	-0.027***	-0.024**	0.008*	-0.014	-0.007	-0.009
	(-3.916)	(-1.533)	(-2.297)	(-1.955)	(-3.489)	(-2.162)	(1.737)	(-0.898)	(-1.616)	(-1.259)
FF4 alpha	0.858	0.313	0.773	0.537	0.616	0.966**	1.145***	1.033**	1.051***	1.045***
	(1.271)	(1.345)	(1.078)	(1.662)	(1.381)	(2.180)	(3.798)	(2.516)	(4.554)	(4.101)
Fund age (log)	-0.043**	-0.011	-0.042	-0.022**	-0.029**	-0.067**	-0.015	-0.101***	-0.016	-0.044**
	(-2.089)	(-1.148)	(-1.258)	(-2.156)	(-2.179)	(-2.686)	(-1.061)	(-3.408)	(-0.934)	(-2.586)
Return volatility	0.429	0.257	2.248*	-0.594	0.352	-1.507	0.184	0.122	-1.194**	-0.755
	(0.481)	(0.557)	(1.713)	(-0.539)	(0.522)	(-1.262)	(0.437)	(0.079)	(-2.522)	(-1.001)
Intercept	6.227***	5.632***	6.285***	5.801***	5.962***	6.234***	5.293***	6.166***	5.641***	5.816***
	(27.67)	(32.90)	(13.33)	(36.78)	(31.55)	(16.03)	(24.92)	(12.54)	(24.37)	(18.93)
Observations	4364	4364	4364	4364	4364	4340	4340	4340	4340	4340
R-squared	0.1488	0.1333	0.17	0.1451	0.1442	0.1457	0.1144	0.155	0.148	0.1505
Adjusted R-squared	0.0615	0.0464	0.0853	0.0599	0.0558	0.0586	0.0227	0.0679	0.0632	0.0646

Table 6-6 (continued)

Panel C:

	High diversification					Low diversification				
Flow-induced trade	1.655*	2.708	6.823***	-0.226	2.123***	3.909**	-0.488	7.414***	-0.774	1.954*
	(1.777)	(1.540)	(4.871)	(-0.317)	(2.827)	(2.634)	(-0.422)	(4.713)	(-0.594)	(1.843)
Return gap	-0.074***	-0.011	-0.068***	-0.036*	-0.046***	-0.006	-0.041	-0.002	-0.031*	-0.021*
	(-5.393)	(-0.782)	(-4.143)	(-1.893)	(-3.741)	(-0.531)	(-1.470)	(-0.204)	(-1.908)	(-1.827)
Fund size (log)	0.029**	0.017***	0.015	0.028***	0.024**	0.042***	0.021***	0.036***	0.031**	0.033***
	(2.091)	(2.951)	(0.960)	(4.135)	(2.477)	(3.130)	(3.760)	(3.445)	(2.661)	(3.858)
Fund family size (log)	-0.033*	0.008*	-0.032*	-0.006	-0.014	-0.016*	-0.003	-0.013	-0.009	-0.010*
	(-1.791)	(1.760)	(-1.787)	(-0.874)	(-1.442)	(-2.010)	(-0.486)	(-0.670)	(-0.713)	(-1.735)
FF4 alpha	0.670	0.769*	0.923	0.610**	0.714*	1.282***	0.691***	0.963	1.047***	1.019***
	(0.804)	(1.861)	(1.145)	(2.646)	(2.015)	(3.173)	(2.902)	(1.287)	(4.066)	(3.162)
Fund age (log)	-0.034	0.014	-0.035	-0.001	-0.012	-0.103***	-0.051***	-0.120***	-0.060***	-0.080***
	(-1.269)	(0.765)	(-0.950)	(-0.097)	(-0.633)	(-4.017)	(-5.943)	(-4.036)	(-4.497)	(-4.846)
Return volatility	-0.270	0.383	1.137	-0.538	0.020	-0.515	0.083	0.944	-0.846	-0.249
	(-0.280)	(1.353)	(0.625)	(-0.617)	(0.039)	(-0.646)	(0.102)	(0.834)	(-1.055)	(-0.333)
Intercept	6.679***	5.293***	6.738***	5.726***	6.063***	6.141***	5.794***	6.052***	5.955***	5.987***
	(14.09)	(42.25)	(11.18)	(33.13)	(20.27)	(21.90)	(35.08)	(14.48)	(40.25)	(27.98)
Observations	4517	4517	4517	4517	4517	4302	4302	4302	4302	4302
R-squared	0.1686	0.1349	0.1883	0.1333	0.1519	0.1573	0.1254	0.168	0.1526	0.165
Adjusted R-squared	0.0861	0.0503	0.107	0.0456	0.0663	0.0695	0.0339	0.0817	0.0657	0.0787

Panel D:

	High reliance on public information					Low reliance on public information				
Flow-induced trade	5.591***	1.438*	10.52***	0.355	3.745***	0.318	2.124*	5.826***	-1.231	1.120
	(3.245)	(1.947)	(3.864)	(0.438)	(2.986)	(0.226)	(1.794)	(4.018)	(-1.660)	(1.483)
Reliance on public information	0.010	-0.007	-0.015	0.011	0.002	-0.030	-0.027*	-0.063**	-0.011	-0.028**
	(0.324)	(-0.252)	(-0.336)	(0.340)	(0.089)	(-1.551)	(-1.852)	(-2.572)	(-1.003)	(-2.591)
Fund size (log)	0.046***	0.014	0.036***	0.030*	0.032***	0.010	0.013**	0.006	0.014**	0.011
	(4.514)	(1.037)	(4.549)	(1.943)	(2.910)	(0.564)	(2.260)	(0.317)	(2.497)	(1.204)

Table 6-6 (continued)

Fund family size (log)	-0.026**	0.011	-0.020	-0.004	-0.009	-0.013	-0.000	-0.011	-0.005	-0.007
	(-2.419)	(0.698)	(-0.919)	(-0.273)	(-1.412)	(-0.884)	(-0.009)	(-0.652)	(-1.030)	(-0.829)
FF4 alpha	1.015***	0.580***	1.126***	0.669***	0.822***	0.986	1.028***	0.777	1.119***	1.005**
	(2.996)	(3.238)	(2.950)	(3.306)	(3.893)	(1.424)	(3.955)	(1.029)	(4.005)	(2.435)
Fund age (log)	-0.069***	-0.051***	-0.066***	-0.058***	-0.061***	-0.040	0.027	-0.070**	0.020	-0.009
	(-3.223)	(-3.298)	(-2.733)	(-4.368)	(-5.061)	(-1.511)	(1.013)	(-2.228)	(0.818)	(-0.430)
Return volatility	-0.429	0.712**	0.553	-0.159	0.078	-0.465	-0.206	1.412	-1.231*	-0.350
	(-0.414)	(2.037)	(0.388)	(-0.200)	(0.110)	(-0.416)	(-0.327)	(0.811)	(-1.842)	(-0.451)
Intercept	6.080***	5.474***	5.992***	5.720***	5.811***	6.404***	5.448***	6.327***	5.805***	5.979***
	(22.87)	(31.78)	(13.44)	(26.74)	(31.22)	(16.74)	(28.30)	(13.67)	(29.84)	(21.43)
Observations	3965	3965	3965	3965	3965	3945	3945	3945	3945	3945
R-squared	0.1378	0.1464	0.1648	0.1569	0.1448	0.1649	0.1378	0.1889	0.1499	0.1648
Adjusted R-squared	0.0417	0.0547	0.0689	0.0681	0.0502	0.0712	0.0422	0.0991	0.0562	0.0723

In Table 6-6, Panel A, for return gap, the results show that funds with a higher return gap appear to trade more in the overall mispricing metric. Flow-induced trade has a positive and significant coefficient of 2.654 (t=3.06) at the 1% level in the higher return gap funds, while its coefficients are not significant at the 10% level in the lower return gap funds, with a coefficient of 1.209 (t=1.421). Higher return gap funds may also trade positively in non-investment anomalies (3.645, t=2.410) and show some evidence of trading in investment anomalies (1.415, t=1.985). While lower return gap funds show an insignificant coefficient of 1.852 (t=1.177) for non-investment anomalies at the 10% level. Both higher return gap funds and lower return gap funds have positive and significant coefficients for prior to 1997 anomalies. Consistent with Kacperczyk, Sialm and Zheng (2008), funds with a higher return gap have advantageous information to assist their trades. I find that funds with higher active skills measured by the return gap appear to exploit anomalies more.

In Panel B, for the industry concentration index (ICI), I find that funds with higher industry concentration appear to exploit stock mispricing. Higher industry concentration funds show a positive and significant coefficient (3.625, t=3.674) at the 1% level for flow-induced trade in the overall mispricing metric, while lower industry concentration funds show an insignificant coefficient of 1.366 (t=1.332) at the 10% level. In addition, higher ICI funds may trade positively in non-investment anomalies (5.179, t=3.195), while lower ICI funds show little evidence of exploiting it (1.44, t=1.124). Both higher ICI funds and lower ICI funds have positive and significant coefficients for prior to 1997 anomalies. The results indicate that higher ICI funds may have the ability to exploit stock return anomalies. Consistent with Kacperczyk, Sialm and Zheng (2005), concentrated invested funds have an informational advantage in specific industries and invest with a distinct style.

In Panel C, for diversification, my findings suggest that higher-diversified funds appear to exploit the overall mispricing metric more, while less-diversified funds appear to trade more in non-investment anomalies. Higher-diversified funds have a positive and significant coefficient of 2.123 (t=2.827) at the 1% level for the overall mispricing metric, while less-diversified funds show an insignificant coefficient of 1.954 (t=1.843) at the 5% level. In the column of non-investment anomalies, diversified funds have a positive coefficient of 1.655 (t=1.777), which is insignificant at the 5% level. Less diversified funds have a positive and significant coefficient of 3.909 (t=2.634) at the 1% level. For prior to 1997 anomalies, both funds have positive and significant coefficients. It implies that diversified funds might exploit a wide range of anomalies (Pollet and Wilson, 2008), while less-diversified funds might trade more on a small group of non-investment in concentrated industry portfolios (Kacperczyk, Sialm and Zheng, 2005).

In Panel D, for reliance on public information (RPI), the results show that fund managers with a higher reliance on analysts' recommendations show better skill in exploring mispricing anomalies. High RPI funds have a positive and significant coefficient for flow-induced trade in the overall mispricing metric of 3.745 (t=2.986), while low RPI funds are insignificant to trade in it (1.120, t=1.483) at the 10% level. Both funds have positive and significant coefficients for prior to 1997 anomalies. Being inconsistent with Kacperczyk and Seru (2007), it might imply that analysts' recommendation might be utilized by fund managers in China to reduce their participation costs (Huang, Wei and Yan, 2004). In this case, smart fund managers might also have the skills to exploit the prior to 1997 anomalies.

In summary, the results support that active funds may have the skills to exploit stock return anomalies. More specifically, funds with higher return gaps and higher industry concentration appear to trade more in composite signals of non-investment anomalies, and the overall mispricing metric. The results are consistent with the idea that fund managers with higher industry concentration and return gap possess an informational advantage in stock picking (Kacperczyk, Sialm and Zheng, 2005; 2008). Also, higher diversification indicates better active skills (Pollet and Wilson, 2008). Well-diversified fund managers appear to exploit the overall mispricing metric as well. Interestingly, funds with a higher reliance on public information also appear to exploit stock return anomalies; this is different from US studies implying that superior funds in China might utilize public information to drive up their existing holdings or reduce their participation costs (Huang, Wei and Yan, 2004). Finally, it shows common evidence that active fund managers may trade on the prior to 1997 anomalies. The findings support the skills of active fund manager exist, as they add values for investors by trading in the right direction of stock return anomalies.

6.5.3.4 Further Robustness Test: Fundamental Fund Characteristics

I further investigate the results of smart trades discussed in the previous section based on fund characteristics including fund size, fund family size, fund performance, fund age and return volatility.

Table 6-7 Sources of Smart Trading Based on Fund Characteristics: Flow-Induced Trade and Stock Return Anomalies

This table reports the Fama-Macbeth (1973) regressions of composite anomaly ranks on flow-induced trade under different fund characteristics. I split the sample based on fund size, fund family size, fund performance (the Fama-French-Carhart alpha), fund age and return volatility. Based on the nine anomalies following Stambaugh, Yu and Yuan (2012), stocks are ranked into ten deciles at the end of each month. I take the value-weight rank of each anomaly as its portfolio anomaly rank. Individual anomalies include total accruals, net operating assets, gross profitability, asset growth, return on assets, investment-to-assets, net stock issues, composite equity issues and momentum. For combinations of anomalies, I take average rank based on individual anomalies. Following Akbas et al. (2015), I define asset growth, investment-to-assets, net operating assets and composite equity issues as investment anomalies. The three anomalies documented by literature prior to 1997 comprise net stock issues (1991), momentum (1993) and total accruals (1996). The six anomalies from 1997 forward comprise net operating assets (2004), investment-to-assets (2004), return on assets (2006), composite equity issues (2006), asset growth (2008) and gross profitability (2010). Control variables include fund size (log), fund family size (log), the Fama-French-Carhart (FF4) alpha, fund age (log) and prior 12 months return volatility. Panel A reports results based on individual anomalies; Panel B reports results based on combinations of anomaly metrics. Standard errors of coefficients are corrected using the Newey-West methods with 12 lags. Coefficients that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Panel A:

Variables	Non-investment anomalies	investment anomalies	Three anomalies documented prior to 1997	Six anomalies from 1997 forward	Overall mispricing metric	Non-investment anomalies	investment anomalies	Three anomalies documented prior to 1997	Six anomalies from 1997 forward	Overall mispricing metric
	Large funds					**Small funds**				
Flow-induced trade	1.630	1.563*	6.092***	-0.644	1.600*	2.461**	-0.255	6.731***	-1.484*	1.253
	(1.204)	(1.881)	(3.602)	(-1.313)	(1.934)	(2.147)	(-0.374)	(5.294)	(-1.785)	(1.621)
Fund size (log)	0.000	0.020	-0.019	0.023*	0.009	0.023	0.021***	0.013	0.027***	0.022**
	(0.023)	(1.603)	(-1.429)	(1.831)	(0.731)	(1.461)	(6.256)	(0.800)	(4.780)	(2.573)
Family size (log)	-0.035	0.008	-0.012	-0.017	-0.015	-0.011**	-0.006	-0.019**	-0.004	-0.009**
	(-1.298)	(0.826)	(-0.382)	(-1.240)	(-0.835)	(-2.484)	(-1.204)	(-2.493)	(-0.573)	(-2.484)
FF4 alpha	1.553**	0.690*	1.503**	1.002***	1.169***	1.237***	0.755***	0.999**	1.035***	1.023***
	(2.646)	(1.784)	(2.526)	(3.198)	(2.962)	(2.998)	(3.062)	(2.289)	(5.068)	(3.811)

Table 6-7 (continued)

Fund age (log)	-0.012	0.000	-0.005	-0.007	-0.006	-0.083***	-0.030***	-0.100**	-0.040***	-0.060***
	(-0.966)	(0.011)	(-0.438)	(-0.751)	(-0.866)	(-2.925)	(-3.221)	(-2.510)	(-3.102)	(-3.785)
Return volatility	0.607	0.623**	2.200	-0.178	0.614	-1.761	0.384	0.322	-1.372***	-0.807
	(0.550)	(2.070)	(1.512)	(-0.170)	(0.961)	(-1.579)	(1.520)	(0.206)	(-3.026)	(-1.162)
Intercept	6.912***	5.179***	6.663***	5.881***	6.142***	6.390***	5.599***	6.544***	5.785***	6.038***
	(9.982)	(19.03)	(9.132)	(24.36)	(15.68)	(20.46)	(42.81)	(15.44)	(38.57)	(30.64)
Observations	5471	5471	5471	5471	5471	5446	5446	5446	5446	5446
R-squared	0.1278	0.1105	0.1335	0.118	0.1168	0.1186	0.0784	0.125	0.0934	0.1108
Adj. R-squared	0.0736	0.0562	0.0787	0.0645	0.0621	0.0648	0.0213	0.0705	0.0377	0.0561
Panel B:										
	Large fund families					**Small fund families**				
Flow-induced trade	1.358	0.146	5.463***	-1.501**	0.820	4.919***	0.516	8.740***	0.073	2.962***
	(0.765)	(0.196)	(3.697)	(-2.157)	(1.017)	(3.096)	(0.772)	(4.903)	(0.102)	(3.227)
Fund size (log)	0.017	0.009	0.005	0.018*	0.014	0.040***	0.018***	0.029**	0.031***	0.030***
	(1.075)	(1.668)	(0.401)	(1.825)	(1.264)	(4.210)	(2.974)	(2.119)	(5.374)	(4.770)
Family size (log)	-0.262***	-0.039	-0.209**	-0.140***	-0.163***	-0.002	0.010	-0.015	0.013	0.003
	(-3.198)	(-1.364)	(-2.536)	(-3.412)	(-3.093)	(-0.306)	(0.880)	(-0.823)	(0.945)	(0.686)
FF4 alpha	1.387**	0.689*	1.225**	1.002***	1.077***	1.313***	0.809***	1.362**	0.952***	1.089***
	(2.129)	(1.834)	(2.146)	(4.141)	(3.229)	(2.741)	(2.945)	(2.494)	(3.280)	(3.028)
Fund age (log)	0.010	-0.008	0.004	0.000	0.002	-0.110***	-0.024*	-0.110***	-0.053***	-0.072***
	(0.492)	(-0.558)	(0.178)	(0.053)	(0.123)	(-4.205)	(-1.945)	(-3.407)	(-3.032)	(-4.234)
Return volatility	-0.105	1.048***	2.108	-0.443	0.407	-0.811	0.247	0.922	-0.972*	-0.340
	(-0.107)	(3.138)	(1.440)	(-0.475)	(0.628)	(-0.715)	(0.719)	(0.585)	(-1.973)	(-0.523)
Intercept	10.99***	6.370***	9.956***	8.431***	8.939***	5.923***	5.335***	6.181***	5.402***	5.662***
	(6.218)	(8.988)	(5.135)	(9.693)	(7.444)	(26.78)	(22.51)	(16.19)	(20.97)	(32.78)
Observations	5569	5569	5569	5569	5569	5348	5348	5348	5348	5348
R-squared	0.1539	0.1011	0.1467	0.1258	0.1497	0.1255	0.0923	0.1466	0.1138	0.1197
Adj. R-squared	0.1028	0.0471	0.0946	0.0735	0.099	0.0695	0.0345	0.0912	0.0577	0.0632

Table 6-7 (continued)

Panel C:

	Well-performing funds					**Under-performing funds**				
Flow-induced trade	2.622	0.261	6.444***	-0.862	1.573	1.069	-0.029	6.135***	-2.196**	0.581
	(1.320)	(0.392)	(3.094)	(-1.022)	(1.285)	(0.877)	(-0.048)	(5.353)	(-2.223)	(0.765)
Fund size (log)	0.034***	0.014**	0.027**	0.024***	0.025***	0.031**	0.016**	0.020	0.026***	0.024***
	(2.732)	(2.448)	(2.394)	(2.972)	(3.036)	(2.524)	(2.239)	(1.610)	(3.487)	(2.898)
Family size (log)	-0.013	0.001	-0.016	-0.001	-0.006	-0.021**	-0.000	-0.020*	-0.007	-0.011
	(-1.531)	(0.197)	(-0.822)	(-0.186)	(-1.011)	(-2.214)	(-0.073)	(-1.807)	(-1.175)	(-1.556)
FF4 alpha	0.703	1.097***	0.419	1.108**	0.878	1.785*	0.796*	1.971*	1.032**	1.345**
	(0.653)	(5.364)	(0.471)	(2.245)	(1.450)	(1.984)	(1.755)	(1.754)	(2.354)	(2.079)
Fund age (log)	-0.068**	-0.002	-0.061*	-0.028*	-0.039*	-0.035**	-0.029**	-0.055**	-0.021*	-0.033***
	(-2.527)	(-0.133)	(-1.829)	(-1.895)	(-1.963)	(-2.159)	(-2.417)	(-2.599)	(-1.886)	(-4.109)
Return volatility	-1.699	0.341	-0.038	-1.169	-0.792	-0.005	0.291	2.301	-0.961*	0.126
	(-1.403)	(0.879)	(-0.025)	(-1.254)	(-0.956)	(-0.005)	(0.668)	(1.601)	(-1.858)	(0.244)
Intercept	6.135***	5.461***	6.087***	5.710***	5.836***	6.094***	5.606***	6.138***	5.747***	5.877***
	(19.34)	(29.27)	(12.51)	(34.24)	(27.41)	(22.02)	(20.44)	(15.94)	(27.52)	(22.80)
Observations	5471	5471	5471	5471	5471	5446	5446	5446	5446	5446
R-squared	0.114	0.0909	0.1184	0.102	0.1089	0.1255	0.0925	0.13	0.1069	0.1209
Adj. R-squared	0.0593	0.0354	0.0638	0.0471	0.0535	0.0714	0.0366	0.0759	0.0525	0.0668

Panel D:

	Old funds					**Young funds**				
Flow-induced trade	1.413	0.622	5.590***	-1.202	1.061	2.992**	0.439	7.034***	-0.730	1.857**
	(1.211)	(1.090)	(3.820)	(-1.366)	(1.586)	(2.458)	(0.725)	(4.611)	(-1.364)	(2.254)
Fund size (log)	0.024**	0.019***	0.018	0.024**	0.022***	0.040***	0.010	0.023**	0.029***	0.027***
	(2.239)	(2.907)	(1.278)	(2.675)	(2.854)	(4.345)	(1.225)	(2.464)	(3.407)	(3.375)

Table 6-7 (continued)

Family size (log)	0.020	0.003	0.014	0.012	0.012	-0.047***	0.003	-0.039**	-0.017**	-0.024***
	(1.227)	(0.307)	(0.575)	(1.374)	(0.927)	(-6.004)	(0.314)	(-2.716)	(-2.167)	(-7.909)
FF4 alpha	1.162*	0.769***	1.297**	0.832***	0.987***	1.456**	0.852*	1.188*	1.187***	1.188**
	(1.865)	(3.355)	(2.501)	(3.228)	(3.145)	(2.588)	(1.993)	(1.883)	(3.139)	(2.644)
Fund age (log)	-0.038	-0.038	0.011	-0.063*	-0.038	-0.019	0.008	-0.018	-0.001	-0.007
	(-0.724)	(-1.626)	(0.176)	(-1.750)	(-1.315)	(-0.881)	(0.323)	(-1.048)	(-0.095)	(-0.535)
Return volatility	-0.640	0.018	2.062	-1.552*	-0.347	-0.812	0.834***	0.464	-0.352	-0.080
	(-0.640)	(0.052)	(1.187)	(-1.962)	(-0.551)	(-0.776)	(2.965)	(0.282)	(-0.723)	(-0.133)
Intercept	5.489***	5.497***	5.214***	5.632***	5.492***	6.427***	5.492***	6.434***	5.800***	6.011***
	(16.35)	(21.15)	(10.52)	(28.10)	(19.03)	(18.62)	(50.83)	(14.36)	(40.62)	(30.89)
Observations	5559	5559	5559	5559	5559	5358	5358	5358	5358	5358
R-squared	0.1312	0.0998	0.1464	0.1212	0.1305	0.1109	0.085	0.1248	0.0962	0.104
Adj. R-squared	0.0794	0.0463	0.0956	0.0694	0.0789	0.0531	0.0261	0.0678	0.0376	0.0453

Panel E:

	Higher volatility					**Low volatility**				
Flow-induced trade	3.594**	0.373	7.695***	-0.603	2.162**	3.022***	2.775***	8.106***	0.316	2.912***
	(2.059)	(0.529)	(3.160)	(-1.415)	(2.226)	(3.087)	(2.721)	(6.865)	(0.352)	(4.195)
Fund size (log)	0.069***	0.019**	0.044***	0.048***	0.047***	0.008	0.019***	0.003	0.018***	0.013*
	(5.753)	(2.353)	(3.352)	(8.200)	(6.730)	(0.626)	(2.929)	(0.210)	(3.123)	(1.756)
Family size (log)	-0.037***	-0.008*	-0.029	-0.022***	-0.024***	0.001	0.007	0.005	0.003	0.004
	(-3.367)	(-1.718)	(-1.624)	(-3.919)	(-3.423)	(0.187)	(1.184)	(0.370)	(0.651)	(0.661)
FF4 alpha	0.983	0.653**	0.876	0.816***	0.836**	1.624***	0.867**	1.700***	1.081***	1.287***
	(1.552)	(2.437)	(1.291)	(3.585)	(2.466)	(3.993)	(2.221)	(3.326)	(3.525)	(3.749)
Fund age (log)	-0.088***	-0.045***	-0.066*	-0.070***	-0.069***	-0.026	-0.002	-0.053**	0.003	-0.015
	(-2.729)	(-3.577)	(-1.733)	(-3.712)	(-3.046)	(-1.375)	(-0.266)	(-2.046)	(0.409)	(-1.309)

Table 6-7 (continued)

Return volatility	-4.575*	-0.782	-3.234	-2.717**	-2.889*	3.111***	1.767	6.446***	0.547	2.514***
	(-1.986)	(-1.522)	(-1.122)	(-2.133)	(-1.967)	(4.047)	(1.622)	(3.809)	(0.837)	(3.563)
Intercept	6.127***	5.847***	6.224***	5.892***	6.002***	5.951***	5.210***	5.768***	5.549***	5.622***
	(17.79)	(28.94)	(11.45)	(34.80)	(23.56)	(15.83)	(47.88)	(13.48)	(36.48)	(23.86)
Observations	5471	5471	5471	5471	5471	5446	5446	5446	5446	5446
R-squared	0.1406	0.0915	0.1392	0.126	0.1325	0.1139	0.0977	0.1244	0.105	0.1148
Adj. R-squared	0.0875	0.0368	0.086	0.0733	0.0792	0.0589	0.0419	0.0705	0.0498	0.0599

In Table 6-7, Panel A, small funds appear to exploit non-investment anomalies more than funds of large size. Small funds have a positive and significant coefficient of 2.461 (t=2.147) for flow-induced trade in non-investment anomalies, while large funds are insignificant to trade in non-investment anomalies (1.630, t=1.204) at the 10% level. In addition, as evidence to exploit stock return anomalies, small funds and large funds show positive coefficients of 6.731 (t=5.294) and 6.092 (t=3.602) for prior to 1997 anomalies which are significant at the 1% level. This is consistent with the literature that demonstrates that small funds tend to outperform large funds (Zheng, 1999; Pollet and Wilson, 2008). The results indicate that the ability to trade on non-investment anomalies might explain the better performance of small funds.

In Panel B, funds in small families appear to trade more in the right direction of anomalies than funds in large families. Funds in small families show positive and significant coefficients for flow-induced trade in the overall mispricing metric (2.962, t=3.227), non-investment anomalies (4.919, t=3.096) and prior to 1997 anomalies (8.740, t=4.903) at the 1% level. While funds in large families show coefficients for flow-induced trade in the overall mispricing metric of 0.820 (t=1.017) and in non-investment anomalies of 1.358 (t=0.765), which are insignificant at the 10% level. Also, funds in large families tend to trade in the wrong direction of 1997 forward anomalies with a negative and significant coefficient of -1.501 (t=2.157) at the 5% level. Both small family funds and large family funds show positive coefficients for prior to 1997 anomalies. This suggests that funds in large families might not find alternative investment opportunities as their size grows (Pollet and Wilson, 2008). Also, these funds might suffer from organizational diseconomies as managers compete to implement their ideas causing hierarchy costs (Chen et al., 2004).

In Panel C, underperforming funds appear to trade in overvalued stocks based on 1997 forward anomalies more than well-performing funds. They show a negative and significant coefficient of -2.196 (t=-2.223) at the 5% level. Both well-performing and under-performing funds tend to trade in prior to 1997 anomalies, they have positive coefficients of 6.444 (t=3.094) and 6.135 (t=5.353) respectively, which are significant at the 1% level. This result is consistent with the idea that well-performing fund may recognize stock return anomalies and trade in undervalued stocks. Also, both under-performing funds and well-performing funds appear to trade in prior to 1997 anomalies such as net stock issues, momentum and total accruals.

In Panel D, young funds appear to trade in the overall mispricing metric. The results show that young funds have a positive and significant coefficient of 1.857(t=2.254) for the overall mispricing metric, while the coefficient of old funds is insignificant at the 10% level (1.061, t=1.586). Also, young funds have a positive coefficient of 2.992 (t=2.458) for non-investment anomalies, which is significant at the 5% level. While old funds have an insignificant coefficient of 1.413 (t=1.211) at the 10% level. Both young funds and old funds appear to trade in prior to 1997 anomalies. They have positive coefficients of 7.034 (t=4.611) and 5.59 (t=3.820) respectively, which are significant at the 1% level. This finding is consistent with the idea that young funds tend to outperform old funds, as active skills evolve over time. New entrants might have new skills or more insights into stock return anomalies (Pástor, Stambaugh and Taylor, 2015).

In Panel E, low volatility funds may trade more in investment anomalies. Lower volatility funds show a positive coefficient of 2.775 (t=2.721), which is significant at the

1% level. While high volatility funds show an insignificant coefficient of 0.373 (t=0.529) at the 10% level. Both lower volatility funds and high volatility funds show positive and significant coefficients for investment anomalies, prior to 1997 anomalies and overall mispricing metric. This is consistent with the idea that low volatility funds might reward their investor with a higher Sharpe ratio. Lower volatility funds might be able to trade in non-investment anomalies.

Overall, the results show that small funds, funds in small fund families, well-performing funds, young funds and low-volatility funds may trade relatively smart in asset pricing anomalies as they tilt towards undervalued stocks based on composite signals of stock return anomalies. The results further support my finding that, on the individual fund level, active fund managers may exhibit skills in exploiting stock return anomalies. Active management adds value for investors from their ability to understand stock mispricing.

6.5.4 FIT and Fund Performance

6.5.4.1 Long-Short Fund Portfolios Sorted by FIT

In this section, to examine whether flow-induced trade has return predictability on fund performance, I define value-weighted flow-induced trade (FIT) across funds' stock holdings as fund-level FIT (Lou, 2012). I then sort funds into ten decile portfolios by their FITs and report equal-weighted and value-weighted returns for holding them from 3 months to 36 months after formation following Jegadeesh and Titman (1993). I adjust returns with the risk-free rate, the Fama-French three-factor model, the Fama-French-Carhart model and the Fama-French five-factor model.

Table 6-8 Long-Short Fund Portfolios Sorted by Flow-Induced Trade

This table reports the returns for fund portfolios ranked by flow-induced trading (FIT). I take value-weighted FIT across stocks as fund-level FIT. The portfolios are rebalanced every quarter and held for three years. At the end of each quarter, funds are sorted into ten deciles based on their flow-induced trade. Equal-weighted and value-weighted monthly portfolio returns for the top decile with the highest FIT, the bottom decile with the lowest FIT and return spreads between the top decile and bottom decile are reported. I follow Jegadeesh and Titman's (1993) method and take equal-weighted average returns across portfolios formed in different quarters to deal with overlapping portfolios in each month. Monthly returns are adjusted with the risk-free rate, the Fama-French model (FF3), the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5). All *t*-statistics are calculated using Newey-West corrections with 12 lags. The returns of spread portfolios that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Equal-weighted						Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles			3-month					3-month		
Top	1.001%	0.571%	0.321%	0.665%	0.272%	1.049%	0.640%	0.453%	0.837%	0.418%
	(1.32)	(2.57)	(1.48)	(2.54)	(1.19)	(1.4)	(2.4)	(1.89)	(2.78)	(1.67)
Bottom	0.502%	0.041%	-0.156%	-0.017%	-0.206%	0.469%	-0.002%	-0.174%	-0.048%	-0.254%
	(0.69)	(0.23)	(-1)	(-0.11)	(-1.23)	(0.63)	(-0.01)	(-0.92)	(-0.24)	(-1.21)
Top-Bottom	0.499%	0.530%	0.477%	0.682%	0.477%	0.580%	0.642%	0.627%	0.885%	0.672%
	(2.3)**	(2.53)**	(2)**	(2.4)**	(1.86)*	(2.38)**	(2.7)***	(2.36)**	(2.77)***	(2.33)**

Equal-weighted						Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles			6-month					6-month		
Top	0.803%	0.379%	0.095%	0.430%	0.055%	0.817%	0.408%	0.185%	0.552%	0.166%
	(1.09)	(2.06)	(0.47)	(2)	(0.25)	(1.12)	(1.98)	(0.9)	(2.36)	(0.73)
Bottom	0.556%	0.095%	-0.114%	-0.005%	-0.170%	0.438%	-0.029%	-0.313%	-0.241%	-0.376%
	(0.76)	(0.54)	(-0.67)	(-0.03)	(-0.95)	(0.57)	(-0.11)	(-0.9)	(-0.65)	(-1.09)
Top-Bottom	0.247%	0.284%	0.208%	0.434%	0.224%	0.379%	0.437%	0.499%	0.792%	0.542%
	(1.29)	(1.55)	(0.94)	(1.68)*	(0.92)	(1.36)	(1.67)*	(1.31)	(1.82)*	(1.41)

Table 6-8 (continued)

	Equal-weighted					Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles			12-month					12-month		
Top	0.740%	0.309%	0.011%	0.326%	-0.035%	0.740%	0.317%	0.086%	0.426%	0.059%
	(1)	(1.69)	(0.06)	(1.67)	(-0.16)	(1.01)	(1.58)	(0.44)	(2.11)	(0.27)
Bottom	0.596%	0.141%	-0.075%	0.035%	-0.125%	0.506%	0.044%	-0.226%	-0.154%	-0.291%
	(0.82)	(0.81)	(-0.46)	(0.2)	(-0.75)	(0.66)	(0.19)	(-0.78)	(-0.5)	(-1.01)
Top-Bottom	0.145%	0.167%	0.086%	0.291%	0.090%	0.234%	0.273%	0.312%	0.580%	0.350%
	(0.83)	(1.05)	(0.44)	(1.38)	(0.41)	(0.99)	(1.26)	(1)	(1.64)	(1.07)

	Equal-weighted					Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles			24-month					24-month		
Top	0.731%	0.287%	0.018%	0.290%	-0.030%	0.715%	0.277%	0.076%	0.365%	0.038%
	(0.99)	(1.64)	(0.11)	(1.59)	(-0.16)	(0.98)	(1.49)	(0.48)	(2.02)	(0.22)
Bottom	0.632%	0.188%	-0.035%	0.102%	-0.094%	0.559%	0.103%	-0.181%	-0.081%	-0.256%
	(0.9)	(1.11)	(-0.22)	(0.61)	(-0.59)	(0.75)	(0.44)	(-0.64)	(-0.27)	(-0.91)
Top-Bottom	0.099%	0.099%	0.053%	0.188%	0.064%	0.155%	0.174%	0.257%	0.447%	0.294%
	(0.66)	(0.74)	(0.34)	(1.07)	(0.35)	(0.74)	(0.91)	(0.92)	(1.36)	(1.02)

Table 6-8 (continued)

	Equal-weighted					Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
FIT deciles	36-month					36-month				
Top	0.495%	0.251%	-0.056%	0.156%	-0.147%	0.539%	0.299%	0.042%	0.247%	-0.037%
	(0.72)	(1.5)	(-0.41)	(1.25)	(-1.02)	(0.78)	(1.8)	(0.34)	(2.01)	(-0.27)
Bottom	0.459%	0.210%	-0.130%	-0.025%	-0.193%	0.413%	0.157%	-0.324%	-0.261%	-0.380%
	(0.66)	(1.2)	(-0.7)	(-0.13)	(-0.95)	(0.55)	(0.7)	(-0.91)	(-0.67)	(-1.02)
Top-Bottom	0.037%	0.041%	0.075%	0.181%	0.046%	0.127%	0.142%	0.366%	0.509%	0.343%
	(0.42)	(0.48)	(0.5)	(1.09)	(0.31)	(0.72)	(0.88)	(1.05)	(1.3)	(0.98)

In Table 6-8, the return spreads remain significant across all risk adjustments over a 3-month horizon. Specifically, it shows a value-weighted four-factor alpha of 0.885% (t=2.36) monthly or 10.62% (t=2.36) annually. In addition, it also shows a value-weighted five-factor alpha of 0.672% (t=2.33) monthly or 8.064% (t=2.33) annually. Also, over a 6-month horizon, it has a value-weighted four-factor alpha of 0.792% (t=1.82) monthly or 9.504 % (t=1.82) annually. However, the return spreads become insignificant when horizons extend to the long term, from 12 months to 36 months. The results indicate that investors may identify flow-induce trade and pick superior funds in the short term. Also, consistent with Coval and Stafford (2007), it might indicate that extreme outflows may reduce the performance of managers if they are forced to trade. The fire sale story in this emerging market may have the same impact on funding performance in the short term within three months. It implies that managers should restrict extreme flows to maintain their performance. Also, investors should identify flow-induced trade as an important criterion in their fund decisions.

6.5.4.2 Do Active Skills Explain the Predictability of FIT for Fund Performance?

To study whether active skills can explain FIT patterns in the short-term predictability of fund performance, I sort funds into 25 portfolios based on flow-induced trade and a group of active skills including industry concentration index, reliance on public information, fund diversification, return gap and active share. I examine whether flow-induced trade remains a significant predictor under different levels of active skills.

Table 6-9 Flow-Induced Trade, Active Skills and Fund Performance

The table reports fund portfolios returns sorted by the flow-induced trade and active investment factors. Active investment factors include fund diversification, reliance on public information, active fund share and industry concentration index. Funds are sorted into 25 portfolios at the end of each month based on FIT and active investment factors. Equal-weighted and value-weighted portfolio returns are adjusted with the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5). All *t*-statistics are corrected using the Newey-West method with 12 lags. The returns of spread portfolios that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Panel A: Industry concentration index

Equal-weighted

ICI quintiles	FIT quintiles							FIT quintiles					
	1	2	3	4	5	(5-1)		1	2	3	4	5	(5-1)
	FF4 alpha							FF5 alpha					
1	-0.05%	0.09%	0.00%	0.12%	0.26%	0.31%		-0.17%	-0.02%	-0.15%	-0.05%	0.06%	0.23%
	(-0.33)	(0.58)	(-0.02)	(0.79)	(1.5)	(2.31)**		(-1.16)	(-0.09)	(-0.88)	(-0.38)	(0.32)	(1.72)*
2	0.14%	0.22%	0.08%	0.12%	0.18%	0.04%		0.09%	0.05%	-0.12%	-0.16%	-0.12%	-0.22%
	(1.05)	(1.37)	(0.48)	(0.79)	(1.34)	(0.27)		(0.67)	(0.27)	(-0.56)	(-0.81)	(-0.8)	(-2.38)**
3	0.13%	0.03%	-0.01%	0.04%	0.16%	0.03%		0.01%	-0.17%	-0.21%	-0.31%	-0.17%	-0.18%
	(0.93)	(0.23)	(-0.04)	(0.26)	(1.31)	(0.21)		(0.08)	(-1.03)	(-1.23)	(-1.86)	(-0.9)	(-1.03)
4	0.03%	0.02%	0.03%	0.12%	0.07%	0.05%		-0.16%	-0.13%	-0.16%	-0.17%	-0.33%	-0.16%
	(0.17)	(0.13)	(0.15)	(0.7)	(0.4)	(0.26)		(-0.92)	(-0.67)	(-0.78)	(-0.8)	(-1.65)	(-1.15)
5	-0.05%	0.06%	0.14%	0.20%	0.19%	0.24%		-0.20%	-0.16%	-0.13%	-0.11%	-0.13%	0.07%
	(-0.27)	(0.32)	(0.62)	(0.78)	(0.86)	(1.25)		(-1.06)	(-0.74)	(-0.57)	(-0.39)	(-0.61)	(0.42)
(5-1)	0.00%	-0.03%	0.14%	0.08%	-0.07%	-0.07%		-0.03%	-0.15%	0.02%	-0.06%	-0.19%	-0.16%
	(0)	(-0.15)	(0.72)	(0.36)	(-0.35)	(-0.37)		(-0.22)	(-0.76)	(0.08)	(-0.21)	(-0.72)	(-0.7)

Table 6-9 (continued)

Value-weighted

ICI quintiles	FIT quintiles 1	2	3	4	5	(5-1)	FIT quintiles 1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	0.08%	0.06%	0.01%	0.16%	0.41%	0.32%	-0.06%	-0.03%	-0.18%	0.05%	0.23%	0.29%
	(0.36)	(0.33)	(0.04)	(0.91)	(1.8)	(1.48)	(-0.24)	(-0.14)	(-0.7)	(0.31)	(0.9)	(1.21)
2	0.20%	0.22%	0.14%	0.26%	0.19%	-0.01%	0.14%	0.06%	-0.04%	0.04%	-0.08%	-0.23%
	(1.3)	(1.27)	(0.78)	(1.12)	(0.85)	(-0.06)	(0.87)	(0.3)	(-0.2)	(0.16)	(-0.34)	(-1.1)
3	0.21%	0.04%	-0.03%	0.07%	0.39%	0.18%	0.13%	-0.16%	-0.21%	-0.23%	0.01%	-0.11%
	(1.44)	(0.23)	(-0.18)	(0.43)	(2.13)	(0.82)	(0.93)	(-0.73)	(-1.43)	(-1.41)	(0.05)	(-0.46)
4	-0.05%	0.08%	-0.03%	-0.07%	0.20%	0.26%	-0.20%	-0.06%	-0.23%	-0.39%	-0.25%	-0.05%
	(-0.35)	(0.34)	(-0.17)	(-0.35)	(1.01)	(1.44)	(-1.29)	(-0.24)	(-1.24)	(-1.55)	(-1.03)	(-0.25)
5	-0.03%	0.08%	0.19%	0.09%	0.39%	0.41%	-0.12%	-0.12%	-0.06%	-0.23%	0.12%	0.24%
	(-0.15)	(0.35)	(0.79)	(0.34)	(1.23)	(1.4)	(-0.65)	(-0.49)	(-0.3)	(-0.76)	(0.5)	(1.23)
(5-1)	-0.11%	0.02%	0.18%	-0.07%	-0.02%	0.09%	-0.06%	-0.09%	0.11%	-0.29%	-0.11%	-0.05%
	(-0.5)	(0.1)	(0.61)	(-0.23)	(-0.08)	(0.28)	(-0.3)	(-0.39)	(0.36)	(-0.77)	(-0.48)	(-0.2)

Panel B: Reliance on public information

Equal-weighted

RPI quintiles	FIT quintiles 1	2	3	4	5	(5-1)	FIT quintiles 1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.18%	0.04%	-0.09%	0.04%	0.12%	0.30%	-0.23%	0.05%	-0.03%	0.22%	0.31%	0.54%
	(-0.56)	(0.27)	(-0.64)	(0.22)	(0.65)	(0.85)	(-0.69)	(0.3)	(-0.14)	(0.89)	(1.31)	(1.25)
2	0.04%	0.02%	0.02%	-0.10%	0.02%	-0.01%	-0.04%	-0.03%	-0.12%	-0.16%	0.18%	0.23%
	(0.21)	(0.13)	(0.12)	(-0.68)	(0.16)	(-0.09)	(-0.27)	(-0.14)	(-0.67)	(-1.06)	(1.05)	(1.53)

Table 6-9 (continued)

3	-0.06%	-0.26%	-0.02%	0.00%	0.08%	0.14%	-0.06%	-0.23%	0.00%	0.03%	0.05%	0.10%
	(-0.42)	(-1.46)	(-0.1)	(0.02)	(0.47)	(0.97)	(-0.33)	(-1.16)	(0.03)	(0.15)	(0.31)	(0.6)
4	-0.10%	-0.16%	-0.03%	0.12%	0.21%	0.31%	-0.12%	-0.18%	-0.12%	0.13%	0.34%	0.47%
	(-0.67)	(-1.07)	(-0.21)	(0.87)	(1.24)	(1.93)*	(-0.77)	(-1.06)	(-0.67)	(0.85)	(1.27)	(1.77)*
5	-0.03%	0.03%	-0.14%	0.01%	0.08%	0.12%	0.06%	0.01%	0.07%	-0.03%	0.13%	0.07%
	(-0.16)	(0.17)	(-0.74)	(0.1)	(0.6)	(0.53)	(0.29)	(0.06)	(0.36)	(-0.21)	(0.57)	(0.24)
(5-1)	0.15%	-0.01%	-0.05%	-0.03%	-0.04%	-0.18%	0.29%	-0.04%	0.09%	-0.26%	-0.18%	-0.47%
	(0.67)	(-0.09)	(-0.29)	(-0.23)	(-0.23)	(-0.67)	(1.1)	(-0.24)	(0.51)	(-1.13)	(-0.86)	(-1.24)

Value-weighted

RPI quintiles			FIT quintiles						FIT quintiles			
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
			FF4 alpha						FF5 alpha			
1	-0.52%	-0.26%	-0.44%	-0.42%	-0.31%	0.20%	-0.51%	-0.24%	-0.34%	-0.15%	-0.03%	0.47%
	(-1.45)	(-1.22)	(-2.43)	(-1.82)	(-1.47)	(0.7)	(-1.44)	(-1.09)	(-1.57)	(-0.52)	(-0.13)	(1.24)
2	-0.27%	-0.29%	-0.31%	-0.55%	-0.43%	-0.15%	-0.34%	-0.36%	-0.40%	-0.57%	-0.29%	0.05%
	(-1.39)	(-1.58)	(-1.24)	(-2.68)	(-2.34)	(-0.9)	(-1.8)	(-1.53)	(-1.74)	(-2.59)	(-1.34)	(0.29)
3	-0.33%	-0.55%	-0.39%	-0.44%	-0.33%	0.01%	-0.31%	-0.51%	-0.34%	-0.47%	-0.37%	-0.06%
	(-1.72)	(-2.53)	(-1.76)	(-2.15)	(-1.56)	(0.04)	(-1.46)	(-2.21)	(-1.45)	(-2)	(-1.9)	(-0.37)
4	-0.30%	-0.43%	-0.36%	-0.28%	-0.21%	0.09%	-0.32%	-0.40%	-0.43%	-0.26%	-0.09%	0.22%
	(-1.75)	(-2.27)	(-1.65)	(-1.37)	(-0.98)	(0.65)	(-1.84)	(-1.93)	(-1.83)	(-1.12)	(-0.33)	(0.96)
5	-0.23%	-0.32%	-0.41%	-0.41%	-0.41%	-0.18%	-0.13%	-0.37%	-0.19%	-0.44%	-0.38%	-0.24%
	(-1.1)	(-1.23)	(-2.22)	(-2.13)	(-1.71)	(-0.95)	(-0.61)	(-1.19)	(-0.91)	(-1.91)	(-1.29)	(-0.92)
(5-1)	0.29%	-0.06%	0.03%	0.00%	-0.09%	-0.38%	0.37%	-0.13%	0.15%	-0.30%	-0.34%	-0.72%
	(1.18)	(-0.44)	(0.26)	(0.01)	(-0.51)	(-1.16)	(1.36)	(-0.73)	(0.8)	(-1.13)	(-1.35)	(-1.72)*

Table 6-9 (continued)

Panel C: Diversification

Equal-weighted

Diversification quintiles	FIT quintiles						FIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.10%	-0.08%	-0.10%	-0.07%	0.19%	0.29%	-0.36%	-0.30%	-0.39%	-0.51%	-0.23%	0.14%
	(-0.67)	(-0.46)	(-0.55)	(-0.56)	(1.3)	(1.95)*	(-1.7)	(-1.39)	(-1.47)	(-2.1)	(-1.02)	(1)
2	-0.14%	-0.08%	-0.03%	0.13%	0.04%	0.17%	-0.38%	-0.36%	-0.34%	-0.25%	-0.36%	0.03%
	(-0.86)	(-0.51)	(-0.2)	(0.78)	(0.25)	(0.89)	(-1.65)	(-1.61)	(-1.69)	(-1.11)	(-1.76)	(0.18)
3	0.02%	0.10%	-0.12%	-0.31%	0.16%	0.15%	-0.25%	-0.23%	-0.35%	-0.77%	-0.23%	0.02%
	(0.12)	(0.68)	(-0.55)	(-1.32)	(0.9)	(0.88)	(-1.18)	(-1)	(-1.38)	(-1.99)	(-1.05)	(0.15)
4	-0.35%	-0.19%	-0.07%	0.01%	0.17%	0.52%	-0.53%	-0.45%	-0.41%	-0.40%	-0.20%	0.33%
	(-0.93)	(-1.19)	(-0.52)	(0.05)	(1)	(1.2)	(-1.4)	(-2.01)	(-1.93)	(-1.67)	(-1.25)	(1)
5	-0.20%	-0.11%	-0.15%	0.10%	0.11%	0.31%	-0.38%	-0.37%	-0.45%	-0.21%	-0.32%	0.05%
	(-1.34)	(-0.91)	(-1.39)	(0.74)	(0.62)	(1.83)*	(-2.22)	(-1.97)	(-2.37)	(-1.16)	(-1.48)	(0.39)
(5-1)	-0.10%	-0.04%	-0.05%	0.18%	-0.08%	0.02%	-0.02%	-0.07%	-0.06%	0.30%	-0.10%	-0.08%
	(-1.12)	(-0.36)	(-0.38)	(1.33)	(-0.58)	(0.12)	(-0.16)	(-0.74)	(-0.4)	(1.71)	(-0.61)	(-0.44)

Value-weighted

Diversification quintiles	FIT quintiles						FIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	0.00%	-0.10%	-0.06%	-0.03%	0.43%	0.43%	-0.20%	-0.28%	-0.35%	-0.46%	0.03%	0.22%
	(0.01)	(-0.44)	(-0.32)	(-0.16)	(2.01)	(2.23)**	(-0.82)	(-1.01)	(-1.36)	(-1.71)	(0.11)	(1.37)
2	-0.10%	-0.10%	0.00%	0.07%	0.16%	0.27%	-0.37%	-0.33%	-0.24%	-0.24%	-0.18%	0.18%
	(-0.59)	(-0.44)	(0.02)	(0.37)	(0.9)	(1.19)	(-1.4)	(-1.16)	(-1.14)	(-0.97)	(-0.87)	(0.84)

Table 6-9 (continued)

3	-0.02%	0.12%	-0.09%	-0.44%	0.32%	0.34%	-0.24%	-0.19%	-0.28%	-0.86%	0.00%	0.24%
	(-0.14)	(0.72)	(-0.38)	(-1.91)	(0.94)	(1)	(-1.24)	(-0.72)	(-1.02)	(-2.26)	(0.01)	(0.75)
4	-0.37%	-0.13%	-0.12%	0.01%	0.28%	0.65%	-0.52%	-0.37%	-0.45%	-0.41%	-0.09%	0.43%
	(-1)	(-0.74)	(-0.89)	(0.04)	(1.3)	(1.64)	(-1.35)	(-1.62)	(-2.23)	(-1.39)	(-0.4)	(1.38)
5	-0.18%	-0.20%	-0.12%	0.17%	0.23%	0.41%	-0.39%	-0.49%	-0.40%	-0.12%	-0.21%	0.18%
	(-1.16)	(-1.46)	(-1.03)	(0.79)	(1.01)	(2.11)**	(-2.13)	(-2.5)	(-2.36)	(-0.52)	(-0.8)	(0.91)
(5-1)	-0.18%	-0.10%	-0.06%	0.20%	-0.21%	-0.02%	-0.19%	-0.21%	-0.05%	0.34%	-0.24%	-0.04%
	(-1.88)*	(-0.63)	(-0.35)	(0.73)	(-1.43)	(-0.13)	(-1.92)	(-1.26)	(-0.27)	(1.02)	(-1.37)	(-0.21)

Panel D: Return gap
Equal-weighted

Return gap quintiles			FIT quintiles						FIT quintiles			
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
			FF4 alpha						FF5 alpha			
1	-0.37%	-0.36%	-0.36%	-0.41%	-0.26%	0.11%	-0.59%	-0.66%	-0.66%	-0.80%	-0.69%	-0.10%
	(-2.3)	(-1.8)	(-2.06)	(-2.74)	(-1.54)	(0.66)	(-3.23)	(-2.48)	(-2.55)	(-3.77)	(-3.06)	(-0.7)
2	-0.17%	-0.07%	-0.03%	-0.09%	0.13%	0.29%	-0.36%	-0.37%	-0.28%	-0.44%	-0.16%	0.20%
	(-1.03)	(-0.47)	(-0.15)	(-0.72)	(0.59)	(1.17)	(-1.79)	(-1.78)	(-1.3)	(-1.89)	(-0.76)	(0.82)
3	0.02%	-0.06%	-0.09%	0.26%	0.19%	0.18%	-0.22%	-0.24%	-0.36%	-0.05%	-0.12%	0.10%
	(0.1)	(-0.32)	(-0.6)	(1.55)	(1.37)	(1.44)	(-1.12)	(-1.29)	(-2.16)	(-0.28)	(-0.66)	(0.78)
4	0.10%	0.09%	0.26%	0.32%	0.46%	0.35%	-0.11%	-0.08%	0.03%	-0.01%	0.14%	0.25%
	(0.66)	(0.76)	(1.62)	(2.17)	(1.86)	(1.37)	(-0.53)	(-0.47)	(0.15)	(-0.06)	(0.71)	(1.08)
5	0.06%	0.27%	0.22%	0.21%	0.26%	0.19%	-0.07%	0.02%	0.01%	-0.02%	-0.06%	0.01%
	(0.41)	(1.72)	(1)	(1.03)	(1.53)	(1.04)	(-0.52)	(0.12)	(0.04)	(-0.09)	(-0.37)	(0.08)
(5-1)	0.44%	0.64%	0.58%	0.62%	0.52%	0.08%	0.52%	0.69%	0.67%	0.78%	0.63%	0.11%
	(4.56)***	(4.25)***	(2.78)***	(4.7)***	(5.25)***	(0.71)	(5.03)***	(4.48)***	(2.97)***	(4.77)***	(5.27)***	(0.92)

Table 6-9 **(continued)**

Value-weighted

Return gap quintiles	FIT quintiles						FIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.34%	-0.37%	-0.32%	-0.46%	-0.12%	0.22%	-0.53%	-0.65%	-0.58%	-0.82%	-0.48%	0.06%
	(-2.52)	(-1.54)	(-1.81)	(-2.92)	(-0.47)	(1.15)	(-3.39)	(-2.43)	(-2.58)	(-3.73)	(-2.08)	(0.34)
2	-0.13%	0.00%	0.05%	-0.18%	0.30%	0.43%	-0.26%	-0.30%	-0.22%	-0.47%	0.06%	0.32%
	(-0.72)	(-0.01)	(0.28)	(-1.09)	(1)	(1.61)	(-1.28)	(-1.21)	(-1)	(-2.03)	(0.2)	(1.12)
3	0.11%	-0.12%	-0.21%	0.23%	0.20%	0.09%	-0.10%	-0.32%	-0.46%	-0.03%	-0.17%	-0.08%
	(0.63)	(-0.64)	(-1.31)	(1.11)	(1.18)	(0.51)	(-0.47)	(-1.44)	(-2.83)	(-0.14)	(-0.92)	(-0.6)
4	0.12%	0.12%	0.20%	0.41%	0.60%	0.48%	-0.13%	-0.08%	-0.01%	0.14%	0.22%	0.35%
	(0.65)	(0.94)	(1.29)	(2.29)	(1.71)	(1.55)	(-0.57)	(-0.53)	(-0.07)	(0.79)	(0.75)	(1.14)
5	0.04%	0.14%	0.20%	0.21%	0.26%	0.22%	-0.08%	-0.07%	0.08%	-0.02%	-0.06%	0.02%
	(0.27)	(0.59)	(0.81)	(0.92)	(1.3)	(0.9)	(-0.6)	(-0.27)	(0.36)	(-0.09)	(-0.32)	(0.09)
(5-1)	0.38%	0.51%	0.53%	0.68%	0.38%	0.00%	0.45%	0.57%	0.66%	0.80%	0.41%	-0.04%
	(3.06)***	(2.59)**	(2.11)**	(4.38)***	(1.78)*	(-0.01)	(4.95)***	(3.25)***	(2.78)***	(4.97)***	(2.22)**	(-0.19)

Panel E: Active share

Equal-weighted

Active share quintiles	FIT quintiles						FIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.44%	-0.32%	-0.33%	-0.21%	-0.06%	0.38%	-0.64%	-0.52%	-0.62%	-0.65%	-0.51%	0.13%
	(-2.65)	(-1.78)	(-1.88)	(-1.13)	(-0.38)	(1.98)*	(-5.32)	(-3.57)	(-5.38)	(-3.98)	(-3.39)	(0.89)
2	-0.31%	-0.28%	-0.25%	0.03%	-0.22%	0.08%	-0.60%	-0.45%	-0.61%	-0.43%	-0.64%	-0.04%
	(-1.85)	(-2.02)	(-1.51)	(0.15)	(-1.2)	(0.64)	(-4.28)	(-2.82)	(-3.26)	(-2.12)	(-3.76)	(-0.33)
3	-0.16%	-0.29%	-0.12%	-0.15%	0.01%	0.17%	-0.37%	-0.68%	-0.44%	-0.53%	-0.33%	0.04%
	(-1.37)	(-1.59)	(-0.86)	(-0.83)	(0.04)	(0.62)	(-3.37)	(-4.17)	(-3.02)	(-3.08)	(-1.03)	(0.16)

Table 6-9 (continued)

4	0.06%	-0.10%	-0.30%	-0.10%	-0.10%	-0.15%	-0.21%	-0.32%	-0.47%	-0.36%	-0.42%	-0.21%
	(0.27)	(-0.6)	(-2.02)	(-0.69)	(-0.41)	(-0.5)	(-0.91)	(-2.11)	(-3.85)	(-2.27)	(-2.75)	(-0.93)
5	0.08%	-0.10%	-0.06%	0.00%	-0.14%	-0.22%	0.00%	-0.18%	-0.12%	-0.19%	-0.16%	-0.16%
	(0.39)	(-0.54)	(-0.24)	(0.01)	(-0.56)	(-1.11)	(-0.01)	(-0.89)	(-0.41)	(-0.89)	(-0.47)	(-0.62)
(5-1)	0.52%	0.22%	0.27%	0.21%	-0.08%	-0.59%	0.64%	0.34%	0.50%	0.46%	0.35%	-0.29%
	(1.98)*	(0.91)	(0.89)	(1.3)	(-0.46)	(-3.03)***	(2.78)***	(1.58)	(1.59)	(3.19)***	(1.29)	(-1.24)
Value-weighted												
Active share quintiles			FIT quintiles						FIT quintiles			
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
			FF4 alpha						FF5 alpha			
1	-0.56%	-0.37%	-0.55%	-0.30%	-0.04%	0.52%	-0.52%	-0.57%	-0.64%	-0.70%	-0.53%	0.00%
	(-2.51)	(-1.52)	(-3.87)	(-1.22)	(-0.25)	(2.13)**	(-3.21)	(-2.76)	(-5.45)	(-2.86)	(-3.56)	(-0.02)
2	-0.19%	-0.22%	-0.11%	-0.05%	-0.13%	0.06%	-0.49%	-0.40%	-0.42%	-0.34%	-0.51%	-0.02%
	(-0.94)	(-1.05)	(-0.59)	(-0.2)	(-0.6)	(0.28)	(-2.77)	(-1.77)	(-2.27)	(-1.15)	(-2.71)	(-0.1)
3	0.01%	-0.47%	-0.19%	-0.13%	0.16%	0.15%	-0.19%	-0.90%	-0.50%	-0.48%	-0.14%	0.04%
	(0.05)	(-1.99)	(-1.01)	(-0.77)	(0.48)	(0.42)	(-0.97)	(-3.98)	(-3.28)	(-2.59)	(-0.34)	(0.13)
4	0.11%	-0.01%	-0.10%	-0.24%	0.07%	-0.04%	-0.17%	-0.31%	-0.30%	-0.49%	-0.33%	-0.16%
	(0.52)	(-0.07)	(-0.61)	(-1.25)	(0.24)	(-0.11)	(-0.86)	(-1.8)	(-1.71)	(-2.6)	(-1.45)	(-0.55)
5	0.15%	-0.10%	-0.24%	-0.08%	0.09%	-0.06%	0.07%	-0.19%	-0.25%	-0.33%	0.08%	0.00%
	(0.71)	(-0.63)	(-1.1)	(-0.3)	(0.27)	(-0.25)	(0.33)	(-1.1)	(-0.92)	(-1.23)	(0.16)	(0)
(5-1)	0.71%	0.26%	0.31%	0.21%	0.13%	-0.58%	0.60%	0.38%	0.39%	0.37%	0.60%	0.01%
	(2)**	(1.19)	(1.33)	(1.08)	(0.46)	(-2.85)**	(2.25)**	(2.07)**	(1.83)*	(1.64)	(1.46)	(0.02)

In Table 6-9, the result shows that the return spreads for FIT show significant results in the first quintile of the industry concentration index (ICI) with an equal-weighted FF4 alpha of 0.31% (t=2.31), in the fourth quintile of reliance on public information (RPI) with an equal-weighted FF4 alpha of 0.31% (t=1.93) and in the first quintile of fund diversification with a value-weighted FF4 alpha of 0.43% (t=2.23). Interestingly, there is little significance of the return spread sorted by FIT. I further sort funds with return gaps and active shares. The long-short spread for return gap has a value-weighted FF5 alpha ranging from 0.41% (t=2.22) to 0.8% (t=4.97), return spread for active share has a value-weighted FF5 alpha ranging from 0.39% (t=1.83) to 0.6% (t=2.25). It implies that the predictability of flow-induced trade might be partially explained by return gaps and active shares.

The findings are consistent with Kacperczyk, Sialm and Zheng (2008) as fund managers with higher return gaps have the ability to cover hidden costs form their transactions that might relate to flow-induced trade. Large fund inflows might induce price pressure on existing holdings while large outflows might cause asset fire sales. The higher return gap funds show skill in handling the impact from flow properly, which might explain flow-induced trade's predictability on fund performance. Also, as money flows in, fund managers with higher active shares have more investment ideas and superior skills in stock selection (Cremers and Petajisto, 2009). Growth of investment ideas may mitigate scale-decreasing returns and indicate better fund performance. Active share also explains the return predictability of the flow-induced mechanism. In sum, the skill to handle hidden costs and accommodate fund flows or to cover other transaction costs and the ability to find alternative investment ideas might partially explain the predictability of the flow-induced trading mechanism.

6.5.5 Robustness Test: Expected FIT Patterns and Fund Performance

6.5.5.1 Construction of Expected FIT: Flow Predictions

From the previous section, I find that trading driven by capital flows significantly affects fund performance. Gruber (1996) finds that the alpha of the four-index model, lagged flows and returns can significantly predict fund flows in the next quarter. Lou (2012) applies the Carhart four-factor alpha to predict fund flows.

As the literature documents that fund flows are predictable (Coval and Staforrd, 2007), I further check the robustness of the flow-induced trading mechanism by replacing actual fund flows with predicted flows. I regress fund flows in quarter *t*+1 on the Fama-French-Carhart alpha, benchmark-adjusted returns and the prior four-quarter fund flows to calculate expected fund flows.[34] I also report decomposed R-squared for each coefficient to explain future fund flows.

$$flow_{i,t+1} = \beta_0 + \beta_1 alpha_{i,t} + \beta_2 ExMkt_{i,t} + \beta_3 flow_{i,t} + \beta_4 flow_{i,t-1} + \beta_5 flow_{i,t-2} + \beta_6 flow_{i,t-3} + \varepsilon_{i,t+1}$$

(Eq. 6-5)

$$E_t[FIT_j] = \frac{\sum_i share_{i,j,t} * E_t[flow_i] * PSF_{i,t}}{\sum_i share_{i,j,t}}$$

(Eq. 6-6)

On the individual stock level, I replace flows with expected flows in constructing the FIT in the previous section. First, expected flows are calculated using the Fama-French-Carhart four-factor alpha, benchmark-adjusted returns and lagged fund flows. At the

[34] Previous literature uses lagged flows, lagged returns and risk-adjusted alpha to predict fund flows (Gruber, 1996; Coval and Stafford, 2007; Shive and Yun, 2013).

fund level, I sum the FIT of all stocks held by fund i and weight them by the shares of a certain stock j in fund i. The expected FIT of the fund is defined as

$$E_t[FIT_i^*] = \sum_j (E_t[FIT_j] * \omega_{i,j,t})$$

(Eq. 6-7)

Table 6-10 Fund Flow Predictions

This table shows predictions of fund flows using the Fama-French-Carhart four-factor alpha, benchmark-adjusted returns and lagged flows. The dependent variable is the quarterly fund flow. $alpha_{i,t}$ is the Fama-French-Carhart four-factor alpha; $ExMkt_{i,t}$ is fund return adjusted with CSI 300 index return. Lagged flows in previous quarters are also included in the regressions. I run the Fama-MacBeth (1973) regressions to get the coefficients. Regarding the Fama-MacBeth regressions, standard errors are adjusted with the Newey-West methods. Decomposed R-squareds (individual R^2 %) calculated using Shapley-own methods are listed for each regression. Coefficients that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Variables	(1) Coeff.	Ind. R^2	(2) Coeff.	Ind. R^2	(3) Coeff.	Ind. R^2	(4) Coeffi.	Ind. R^2
$Alpha_{i,t}$	0.551***	34.85			0.491***	31.06	0.593***	27.44
	(2.719)				(3.011)		(4.597)	
$ExMkt_{i,t}$			0.609**	21.84	0.588**	17.46	0.569**	16.15
			(2.677)		(2.691)		(2.502)	
$Flow_{i,t}$	0.098***	65.15	0.079***	78.16	0.076***	51.47	0.073***	44.83
	(4.818)		(4.830)		(4.298)		(5.228)	
$Flow_{i,t-1}$							0.035***	3.43
							(3.714)	
$Flow_{i,t-2}$							-0.007	8.11
							(-0.332)	
$Flow_{i,t-3}$							-0.059	0.04
							(-1.327)	
$Intercept$	0.023		0.033		0.030		0.009	
	(0.809)		(1.021)		(0.960)		(0.572)	
Observations	7896		7896		7896		7896	
R-squared	0.0437		0.0420		0.06		0.1021	
Adj. R-squared	0.0281		0.0263		0.0366		0.056	

In Table 6-10, Column 3, I find that the Fama-French-Carhart alpha, benchmark-adjusted returns and lagged fund flows positively predict fund flows. The dependent variable is quarterly fund flow, as defined in Equation 6-1. It is measured as the rate of growth in net assets from quarter *t*-1 to quarter *t*. The Fama-French-Carhart alpha has a significant coefficient of 0.491 (t=3.011) at the 1% level and a decomposed R-squared 31.06%. For example, it suggests that 1% increase in the Fama-French-Carhart alpha is associated with an average of 0.491% increase in fund flows. Benchmark-adjusted returns have a significant coefficient of 0.588 (t=2.691) at the 1% level and a decomposed R-squared of 17.46%. Lagged fund flows have a significant coefficient of 0.076% (t=4.298) at the 1% level and a decomposed R-squared of 51.47%. I further take the specification (3) to obtain expected fund flows, then construct expected flow-induced trade to check the robustness of performance predictability.

6.5.5.2 Expected FIT and Fund performance

Table 6-11 Long-Short Fund Portfolios Sorted by Expected Flow-Induced Trade

This table reports the returns for fund portfolios ranked by expected flow-induced trading (EFIT). I take value-weighted EFIT across stocks as fund-level EFIT. The portfolios are rebalanced every quarter and held for three years. At the end of each quarter, funds are sorted into ten deciles based on flow-induced trade. Equal-weighted and value-weighted monthly portfolio returns of the top decile with the highest EFIT, the bottom decile with the lowest EFIT and the spread between top decile and bottom decile are reported. I follow Jegadeesh and Titman's (1993) method and take equal-weighted average return across portfolios formed in different quarters to deal with overlapping portfolios in each month. Monthly returns are adjusted with the risk-free rate, the Fama-French model (FF3), the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5). All *t*-statistics are calculated using Newey-West corrections with 12 lags. The returns of spread portfolios that are significant at the 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Equal-weighted						Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
EFIT deciles			3-month					3-month		
Top	0.391%	0.415%	-0.002%	0.221%	-0.073%	0.467%	0.490%	0.136%	0.325%	0.083%
	(0.46)	(1.61)	(-0.01)	(1.23)	(-0.37)	(0.53)	(1.64)	(0.58)	(1.44)	(0.34)
Bottom	0.006%	0.025%	-0.381%	-0.154%	-0.507%	-0.181%	-0.164%	-0.475%	-0.265%	-0.582%
	(0.01)	(0.12)	(-1.59)	(-0.73)	(-1.88)	(-0.28)	(-0.73)	(-1.75)	(-1.16)	(-1.86)
Top-Bottom	0.385%	0.389%	0.379%	0.375%	0.434%	0.648%	0.654%	0.611%	0.591%	0.665%
	(1.06)	(1.23)	(1.13)	(1.27)	(1.24)	(1.42)	(1.66)*	(1.45)	(1.65)*	(1.5)

Equal-weighted						Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
EFIT deciles			6-month					6-month		
Top	0.329%	0.359%	-0.047%	0.179%	-0.086%	0.371%	0.401%	0.052%	0.253%	0.030%
	(0.39)	(1.78)	(-0.32)	(1.24)	(-0.55)	(0.43)	(1.84)	(0.32)	(1.6)	(0.18)
Bottom	0.144%	0.167%	-0.234%	-0.005%	-0.316%	-0.044%	-0.022%	-0.314%	-0.121%	-0.376%
	(0.21)	(1.03)	(-1.61)	(-0.03)	(-2.19)	(-0.07)	(-0.15)	(-2.03)	(-0.84)	(-2.31)
Top-Bottom	0.186%	0.192%	0.186%	0.184%	0.229%	0.415%	0.424%	0.366%	0.374%	0.407%
	(0.87)	(1.47)	(1.31)	(1.38)	(1.66)*	(1.39)	(2.14)**	(1.84)*	(2.27)**	(2.15)**

Table 6-11 (continued)

	Equal-weighted					Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
EFIT deciles			12-month					12-month		
Top	0.735%	0.267%	-0.034%	0.200%	-0.062%	0.774%	0.299%	0.050%	0.266%	0.033%
	(1.1)	(1.33)	(-0.23)	(1.25)	(-0.4)	(1.11)	(1.39)	(0.32)	(1.61)	(0.21)
Bottom	0.510%	0.129%	-0.246%	0.009%	-0.327%	0.381%	0.033%	-0.239%	-0.030%	-0.298%
	(0.93)	(0.72)	(-1.53)	(0.06)	(-1.95)	(0.73)	(0.2)	(-1.43)	(-0.18)	(-1.67)
Top-Bottom	0.225%	0.138%	0.212%	0.191%	0.265%	0.393%	0.266%	0.289%	0.296%	0.331%
	(1.3)	(1.03)	(1.51)	(1.5)	(1.87)*	(1.7)*	(1.55)	(1.71)*	(2.15)**	(1.99)*

	Equal-weighted					Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
EFIT deciles			24-month					24-month		
Top	0.620%	0.227%	-0.051%	0.091%	0.007%	0.652%	0.250%	0.027%	0.159%	0.089%
	(0.96)	(1.05)	(-0.3)	(0.57)	(0.04)	(0.96)	(1.07)	(0.15)	(0.91)	(0.47)
Bottom	0.483%	0.161%	-0.211%	-0.042%	-0.223%	0.414%	0.130%	-0.126%	0.020%	-0.121%
	(0.89)	(0.87)	(-1.42)	(-0.35)	(-1.42)	(0.81)	(0.77)	(-0.86)	(0.14)	(-0.74)
Top-Bottom	0.138%	0.066%	0.160%	0.133%	0.230%	0.238%	0.120%	0.153%	0.139%	0.210%
	(0.95)	(0.62)	(1.6)	(1.23)	(2.84)***	(1.13)	(0.8)	(1.13)	(0.99)	(1.68)*

Table 6-11 (continued)

	Equal-weighted					Value-weighted				
	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha	Excess return	CAPM alpha	FF3 alpha	FF4 alpha	FF5 alpha
EFIT deciles	36-month					36-month				
Top	0.739%	0.127%	-0.101%	0.021%	-0.060%	0.769%	0.144%	-0.016%	0.101%	0.027%
	(0.99)	(0.58)	(-0.55)	(0.12)	(-0.32)	(0.98)	(0.61)	(-0.08)	(0.52)	(0.14)
Bottom	0.652%	0.143%	-0.233%	-0.076%	-0.219%	0.574%	0.135%	-0.127%	0.007%	-0.116%
	(1.01)	(0.71)	(-1.35)	(-0.56)	(-1.22)	(0.95)	(0.72)	(-0.73)	(0.04)	(-0.6)
Top-Bottom	0.087%	-0.016%	0.132%	0.097%	0.159%	0.195%	0.009%	0.110%	0.094%	0.144%
	(0.63)	(-0.17)	(1.55)	(1.14)	(2.26)**	(0.93)	(0.06)	(0.79)	(0.65)	(1.1)

To check the robustness of the predictability of flow-induced trade with expected fund flows, I sort funds based on expected flow-induced trade (EFIT) into ten decile portfolios; I then construct a long-short portfolio by longing the highest EFIT funds and shorting the lowest EFIT funds. Equal-weighted and value-weighted returns are reported in Table 6-11. I find that the long-short fund portfolio shows a significant and positive value-weighted FF4 alpha of 0.374% (t=2.27) over a 6-month horizon and a FF4 alpha of 0.296% (t=2.15) over a 12-month horizon. Consistent with my analysis in Table 6-8, the EFIT confirms the fund return predictability of the flow-induced mechanism. It also suggests that expected fund flows might enhance the performance predictability of the flow-induced trade mechanism in the longer term (exceeds six months). This might be attributed to expected fund flows based on fund flow being sticky (Coval and Staffod, 2007) or the smart money effect having a more persistent impact on the flow-induced trading mechanism. (Gruber, 1996; Zheng, 1999; Kewani and Stolin, 2008).

6.5.5.3 Expected FIT and Active Skills

Table 6-12 Expected Flow-Induced Trade, Active skills and Fund performance

The table reports fund portfolios' returns sorting by flow-induced trade and active investment factors. Active investment factors include fund diversification, reliance on public information, active fund share and industry concentration index. Funds are sorted into 25 portfolios at the end of each month based on FIT and active investment factors. Equal-weighted and value-weighted portfolio risk-adjusted returns are reported with the Fama-French-Carhart model (FF4) and the Fama-French five-factor model (FF5). All *t*-statistics are corrected using Newey-West methods with 12 lags. The returns of spread portfolios that are significant at 1%, 5% and 10% levels are indicated with ***, ** and * respectively.

Panel A: Industry concentration index

Equal-weighted

ICI quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.09%	0.06%	-0.05%	0.11%	0.36%	0.45%	-0.32%	-0.15%	-0.23%	0.01%	0.17%	0.49%
	(-0.64)	(0.47)	(-0.38)	(0.6)	(1.38)	(1.35)	(-2.22)	(-1.23)	(-1.52)	(0.06)	(0.6)	(1.31)
2	0.01%	0.09%	0.18%	0.12%	0.28%	0.27%	-0.39%	-0.22%	-0.06%	-0.05%	0.17%	0.55%
	(0.08)	(0.53)	(1.07)	(0.77)	(1.78)	(1.38)	(-1.59)	(-1.11)	(-0.35)	(-0.3)	(0.87)	(2.15)**
3	-0.14%	-0.06%	0.03%	0.14%	0.15%	0.29%	-0.57%	-0.37%	-0.23%	-0.12%	-0.12%	0.46%
	(-0.79)	(-0.44)	(0.24)	(0.86)	(1.18)	(1.57)	(-2.81)	(-1.98)	(-1.28)	(-0.67)	(-0.81)	(2.7)**
4	-0.23%	0.18%	-0.18%	0.15%	0.00%	0.23%	-0.61%	-0.09%	-0.53%	-0.21%	-0.27%	0.34%
	(-1.09)	(1.07)	(-1.02)	(0.8)	(-0.01)	(1.07)	(-2.26)	(-0.45)	(-2.23)	(-0.92)	(-1.74)	(1.37)
5	0.01%	0.20%	0.10%	0.15%	0.06%	0.05%	-0.35%	-0.19%	-0.25%	-0.17%	-0.27%	0.08%
	(0.03)	(1.01)	(0.45)	(0.68)	(0.32)	(0.28)	(-1.46)	(-0.9)	(-1.03)	(-0.7)	(-1.38)	(0.39)
(5-1)	0.10%	0.13%	0.15%	0.04%	-0.30%	-0.40%	-0.03%	-0.05%	-0.02%	-0.19%	-0.44%	-0.41%
	(0.82)	(0.86)	(0.7)	(0.27)	(-1.91)*	(-1.86)*	(-0.15)	(-0.22)	(-0.08)	(-0.79)	(-1.96)*	(-1.62)

Table 6-12 (continued)

Value-weighted

ICI quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.20%	0.06%	-0.05%	0.17%	0.42%	0.62%	-0.40%	-0.14%	-0.17%	0.05%	0.28%	0.68%
	(-1.15)	(0.43)	(-0.24)	(0.7)	(1.28)	(1.42)	(-1.95)	(-0.97)	(-0.88)	(0.18)	(0.75)	(1.29)
2	0.09%	0.02%	0.24%	0.07%	0.48%	0.38%	-0.29%	-0.30%	0.01%	-0.07%	0.37%	0.66%
	(0.62)	(0.07)	(1.41)	(0.38)	(1.93)	(1.51)	(-1.38)	(-1.31)	(0.06)	(-0.45)	(1.29)	(2.14)**
3	-0.15%	-0.07%	0.13%	0.20%	0.24%	0.39%	-0.55%	-0.27%	-0.09%	-0.06%	0.04%	0.59%
	(-0.65)	(-0.52)	(0.8)	(1.17)	(1.34)	(1.59)	(-2.68)	(-1.59)	(-0.47)	(-0.32)	(0.22)	(2.4)**
4	-0.41%	0.10%	-0.26%	0.19%	0.06%	0.47%	-0.80%	-0.16%	-0.54%	-0.13%	-0.21%	0.59%
	(-1.48)	(0.55)	(-1.56)	(0.86)	(0.4)	(1.53)	(-2.34)	(-0.87)	(-2.93)	(-0.51)	(-1.44)	(1.72)*
5	-0.01%	0.24%	-0.01%	0.07%	0.12%	0.14%	-0.36%	-0.09%	-0.24%	-0.23%	-0.14%	0.22%
	(-0.07)	(1.06)	(-0.05)	(0.27)	(0.73)	(0.76)	(-1.46)	(-0.41)	(-1.03)	(-0.89)	(-0.78)	(0.98)
(5-1)	0.19%	0.18%	0.04%	-0.10%	-0.30%	-0.49%	0.03%	0.05%	-0.07%	-0.28%	-0.42%	-0.46%
	(0.86)	(1.01)	(0.12)	(-0.48)	(-1.29)	(-1.34)	(0.15)	(0.27)	(-0.27)	(-1.04)	(-1.42)	(-1.17)

Panel B: Reliance on public information

Equal-weighted

RPI quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.06%	-0.12%	-0.07%	0.28%	0.20%	0.26%	-0.42%	-0.35%	-0.31%	-0.05%	-0.07%	0.36%
	(-0.39)	(-0.5)	(-0.46)	(1.76)	(0.87)	(1.05)	(-2.05)	(-1.27)	(-1.49)	(-0.23)	(-0.26)	(1.37)
2	-0.29%	-0.04%	0.00%	0.13%	0.08%	0.37%	-0.56%	-0.36%	-0.31%	-0.10%	-0.21%	0.35%
	(-1.91)	(-0.43)	(0.02)	(0.93)	(0.63)	(1.91)*	(-2.69)	(-2.03)	(-1.5)	(-0.49)	(-1.2)	(1.75)*

Table 6-12 (continued)

3	-0.22%	0.12%	0.02%	-0.03%	0.08%	0.30%	-0.53%	-0.16%	-0.28%	-0.23%	-0.21%	0.33%
	(-1.35)	(0.89)	(0.14)	(-0.2)	(0.47)	(1.3)	(-2.31)	(-0.84)	(-1.44)	(-1.22)	(-1.01)	(1.32)
4	-0.03%	0.08%	-0.11%	0.07%	0.15%	0.18%	-0.32%	-0.19%	-0.38%	-0.14%	-0.03%	0.29%
	(-0.2)	(0.62)	(-0.68)	(0.4)	(1.09)	(0.83)	(-1.41)	(-1.05)	(-1.7)	(-0.68)	(-0.18)	(1.15)
5	-0.08%	-0.03%	0.04%	0.22%	0.16%	0.25%	-0.40%	-0.21%	-0.25%	-0.04%	-0.11%	0.29%
	(-0.47)	(-0.15)	(0.32)	(1.28)	(1.08)	(1.17)	(-1.67)	(-1.04)	(-1.36)	(-0.2)	(-0.59)	(1.47)
(5-1)	-0.02%	0.09%	0.10%	-0.06%	-0.03%	-0.01%	0.02%	0.14%	0.07%	0.01%	-0.05%	-0.07%
	(-0.15)	(0.49)	(0.97)	(-0.71)	(-0.21)	(-0.07)	(0.16)	(0.59)	(0.59)	(0.06)	(-0.23)	(-0.39)

Value-weighted

RPI quintiles			EFIT quintiles						EFIT quintiles			
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
			FF4 alpha						FF5 alpha			
1	0.06%	0.01%	-0.16%	0.32%	0.39%	0.33%	-0.26%	-0.19%	-0.35%	0.03%	0.17%	0.43%
	(0.32)	(0.05)	(-0.96)	(1.47)	(1.47)	(1.16)	(-1.32)	(-0.66)	(-1.58)	(0.12)	(0.57)	(1.41)
2	-0.39%	-0.08%	-0.09%	0.10%	0.08%	0.47%	-0.65%	-0.35%	-0.32%	-0.14%	-0.19%	0.45%
	(-2.13)	(-0.66)	(-0.54)	(0.72)	(0.48)	(1.75)*	(-2.77)	(-1.98)	(-1.39)	(-0.65)	(-0.94)	(1.54)
3	-0.49%	0.04%	-0.03%	-0.02%	0.21%	0.70%	-0.81%	-0.27%	-0.27%	-0.20%	-0.05%	0.75%
	(-2.95)	(0.24)	(-0.2)	(-0.15)	(1.02)	(2.52)**	(-3.05)	(-1.32)	(-1.44)	(-1.4)	(-0.24)	(2.41)**
4	0.05%	0.08%	-0.06%	0.01%	0.10%	0.05%	-0.25%	-0.17%	-0.30%	-0.16%	-0.04%	0.21%
	(0.29)	(0.63)	(-0.28)	(0.07)	(0.82)	(0.24)	(-0.97)	(-0.99)	(-1.26)	(-0.78)	(-0.27)	(0.86)
5	-0.02%	0.19%	0.09%	0.28%	0.19%	0.21%	-0.36%	-0.01%	-0.15%	0.03%	-0.10%	0.26%
	(-0.11)	(0.79)	(0.65)	(1.46)	(1.08)	(0.79)	(-1.19)	(-0.04)	(-0.85)	(0.12)	(-0.53)	(0.89)
(5-1)	-0.08%	0.17%	0.25%	-0.03%	-0.20%	-0.11%	-0.10%	0.18%	0.20%	-0.01%	-0.27%	-0.17%
	(-0.37)	(0.87)	(2.1)**	(-0.19)	(-1.15)	(-0.46)	(-0.38)	(0.94)	(1.58)	(-0.03)	(-1.28)	(-0.62)

Table 6-12 (continued)

Panel C: Diversification

Equal-weighted

Diversification quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.19%	-0.02%	0.05%	0.34%	0.14%	0.34%	-0.53%	-0.25%	-0.30%	0.04%	-0.13%	0.40%
	(-1.32)	(-0.1)	(0.25)	(1.44)	(0.68)	(1.44)	(-2.73)	(-1.33)	(-1.3)	(0.16)	(-0.63)	(1.64)
2	-0.11%	0.20%	-0.04%	0.12%	0.05%	0.16%	-0.48%	-0.08%	-0.35%	-0.21%	-0.24%	0.23%
	(-0.73)	(1.21)	(-0.27)	(0.63)	(0.23)	(0.78)	(-2.23)	(-0.42)	(-1.93)	(-0.96)	(-1.04)	(0.99)
3	-0.12%	0.07%	0.09%	0.09%	0.18%	0.29%	-0.42%	-0.24%	-0.17%	-0.27%	-0.11%	0.30%
	(-0.85)	(0.31)	(0.57)	(0.46)	(0.93)	(1.66)*	(-2.27)	(-1.01)	(-0.92)	(-1.25)	(-0.5)	(1.37)
4	-0.10%	-0.30%	0.04%	0.09%	0.24%	0.34%	-0.39%	-0.61%	-0.26%	-0.16%	-0.05%	0.34%
	(-0.47)	(-1.11)	(0.22)	(0.5)	(1.44)	(1.58)	(-1.59)	(-2.18)	(-1.2)	(-0.83)	(-0.27)	(1.44)
5	-0.24%	-0.05%	-0.05%	0.03%	0.20%	0.44%	-0.58%	-0.33%	-0.33%	-0.20%	-0.05%	0.53%
	(-1.41)	(-0.3)	(-0.36)	(0.19)	(0.9)	(1.69)*	(-2.5)	(-1.78)	(-1.98)	(-1.22)	(-0.23)	(1.81)*
(5-1)	-0.05%	-0.03%	-0.10%	-0.32%	0.06%	0.11%	-0.04%	-0.08%	-0.03%	-0.25%	0.08%	0.13%
	(-0.47)	(-0.34)	(-1.02)	(-2.24)**	(0.33)	(0.51)	(-0.41)	(-0.85)	(-0.34)	(-1.5)	(0.48)	(0.62)

Value-weighted

Diversification quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.04%	0.12%	0.10%	0.50%	0.24%	0.28%	-0.41%	-0.05%	-0.23%	0.18%	0.01%	0.42%
	(-0.26)	(0.69)	(0.64)	(1.5)	(0.91)	(0.9)	(-2.12)	(-0.27)	(-1.17)	(0.49)	(0.04)	(1.3)
2	-0.20%	0.16%	-0.05%	0.19%	0.00%	0.20%	-0.52%	-0.11%	-0.29%	-0.09%	-0.24%	0.28%
	(-1.1)	(1.15)	(-0.24)	(0.74)	(0)	(0.94)	(-2.35)	(-0.61)	(-1.17)	(-0.34)	(-0.94)	(1.13)
3	-0.13%	0.16%	0.01%	-0.03%	0.34%	0.47%	-0.45%	-0.11%	-0.18%	-0.34%	0.11%	0.56%
	(-0.84)	(0.63)	(0.06)	(-0.19)	(1.13)	(1.56)	(-2.08)	(-0.39)	(-1.02)	(-1.56)	(0.32)	(1.53)

Table 6-12 (continued)

4	-0.21%	-0.32%	-0.09%	0.13%	0.31%	0.53%	-0.44%	-0.67%	-0.32%	-0.12%	0.05%	0.49%
	(-0.95)	(-1.47)	(-0.41)	(0.79)	(1.58)	(2.05)**	(-1.61)	(-2.83)	(-1.31)	(-0.66)	(0.21)	(1.72)*
5	-0.21%	-0.17%	-0.16%	0.05%	0.25%	0.46%	-0.59%	-0.42%	-0.39%	-0.19%	0.02%	0.61%
	(-0.9)	(-0.96)	(-1.14)	(0.28)	(0.94)	(1.38)	(-2.11)	(-2.07)	(-2.68)	(-0.94)	(0.07)	(1.61)
(5-1)	-0.17%	-0.29%	-0.26%	-0.45%	0.01%	0.18%	-0.18%	-0.36%	-0.17%	-0.37%	0.01%	0.19%
	(-1.17)	(-2.34)**	(-2.36)**	(-1.85)*	(0.05)	(0.67)	(-1.36)	(-2.88)***	(-1.43)	(-1.43)	(0.04)	(0.76)

Panel D: Return gap

Equal-weighted

Return gap quintiles			EFIT quintiles						EFIT quintiles			
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
			FF4 alpha						FF5 alpha			
1	-0.73%	-1.44%	-0.47%	-0.18%	-0.12%	0.61%	-1.13%	-1.73%	-0.87%	-0.55%	-0.44%	0.70%
	(-3.07)	(-1.79)	(-3.35)	(-0.77)	(-0.7)	(2.33)**	(-3.02)	(-2.37)	(-2.95)	(-1.7)	(-2.04)	(2.37)**
2	-0.19%	-0.14%	-0.09%	0.00%	0.23%	0.42%	-0.58%	-0.47%	-0.43%	-0.38%	0.01%	0.59%
	(-1.18)	(-1.09)	(-0.61)	(-0.02)	(1.05)	(1.35)	(-2.05)	(-1.89)	(-1.71)	(-1.57)	(0.03)	(1.49)
3	-0.01%	0.09%	0.04%	0.07%	0.07%	0.08%	-0.34%	-0.21%	-0.28%	-0.23%	-0.24%	0.10%
	(-0.03)	(0.56)	(0.27)	(0.54)	(0.34)	(0.29)	(-1.2)	(-0.92)	(-1.35)	(-1.2)	(-0.93)	(0.37)
4	0.21%	0.21%	0.23%	0.23%	0.09%	-0.12%	-0.14%	0.00%	-0.04%	-0.09%	-0.28%	-0.15%
	(1.29)	(0.95)	(1.81)	(1.49)	(0.87)	(-0.63)	(-0.5)	(0.01)	(-0.24)	(-0.38)	(-1.16)	(-0.68)
5	0.00%	0.49%	0.24%	0.23%	0.31%	0.31%	-0.30%	0.24%	-0.10%	-0.05%	0.00%	0.30%
	(0)	(3.44)	(1.67)	(1.18)	(1.93)	(1.47)	(-1.56)	(1.32)	(-0.48)	(-0.16)	(-0.01)	(1.4)
(5-1)	0.73%	1.93%	0.70%	0.41%	0.42%	-0.30%	0.83%	1.96%	0.77%	0.50%	0.43%	-0.40%
	(3.17)***	(2.47)**	(5.02)***	(2.58)**	(3.12)***	(-1.59)	(3.12)***	(3)***	(4.68)***	(3.37)***	(5.95)***	(-1.48)

Table 6-12 (continued)

Value-weighted

Return gap quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.76%	-1.65%	-0.54%	-0.28%	0.03%	0.79%	-1.09%	-1.90%	-0.89%	-0.60%	-0.20%	0.90%
	(-3.2)	(-1.88)	(-3.94)	(-1.1)	(0.13)	(2.51)**	(-3.22)	(-2.4)	(-3.53)	(-1.84)	(-0.74)	(2.58)**
2	-0.28%	-0.11%	-0.11%	-0.03%	0.38%	0.66%	-0.69%	-0.41%	-0.42%	-0.33%	0.20%	0.89%
	(-1.37)	(-0.77)	(-0.78)	(-0.14)	(1.21)	(1.52)	(-1.91)	(-1.61)	(-1.88)	(-1.25)	(0.58)	(1.59)
3	-0.18%	0.12%	-0.03%	-0.05%	0.22%	0.40%	-0.49%	-0.20%	-0.27%	-0.32%	-0.04%	0.45%
	(-0.84)	(0.7)	(-0.15)	(-0.44)	(0.66)	(0.97)	(-1.51)	(-0.96)	(-1.14)	(-1.66)	(-0.11)	(1)
4	0.23%	0.19%	0.17%	0.18%	0.25%	0.01%	-0.12%	-0.07%	-0.09%	-0.16%	-0.11%	0.01%
	(1)	(1.23)	(1.16)	(1.32)	(1.76)	(0.05)	(-0.36)	(-0.38)	(-0.46)	(-0.75)	(-0.51)	(0.02)
5	0.01%	0.37%	0.19%	0.27%	0.23%	0.23%	-0.26%	0.16%	-0.06%	-0.02%	-0.02%	0.24%
	(0.03)	(2.34)	(1.02)	(1.1)	(1.41)	(0.88)	(-1.1)	(0.86)	(-0.26)	(-0.06)	(-0.08)	(0.86)
(5-1)	0.76%	2.03%	0.73%	0.55%	0.20%	-0.56%	0.84%	2.06%	0.83%	0.58%	0.18%	-0.65%
	(3.15)***	(2.3)**	(4.4)***	(2.59)**	(1.19)	(-2.31)**	(3.49)***	(2.78)***	(5.86)***	(2.7)***	(1.4)	(-2.35)**

Panel E: Active share

Equal-weighted

Active share quintiles	EFIT quintiles						EFIT quintiles					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
	FF4 alpha						FF5 alpha					
1	-0.38%	-0.08%	0.01%	-0.04%	-0.16%	0.22%	-0.61%	-0.04%	-0.02%	-0.04%	-0.17%	0.44%
	(-1.76)	(-0.33)	(0.03)	(-0.22)	(-0.96)	(0.75)	(-2.15)	(-0.14)	(-0.05)	(-0.15)	(-1.07)	(1.21)
2	-0.18%	-0.12%	-0.44%	-0.09%	-0.06%	0.12%	-0.19%	0.02%	-0.20%	-0.04%	-0.09%	0.10%
	(-1.12)	(-0.58)	(-3.02)	(-0.58)	(-0.38)	(0.83)	(-1.14)	(0.09)	(-1.07)	(-0.26)	(-0.49)	(0.79)
3	-0.17%	-0.20%	-0.21%	0.18%	0.17%	0.34%	-0.26%	-0.31%	-0.33%	0.24%	0.26%	0.52%
	(-1.15)	(-1.31)	(-1.51)	(1.22)	(0.96)	(1.66)*	(-1.69)	(-2.32)	(-2.2)	(1.36)	(1.06)	(1.7)*

Table 6-12 (continued)

4	-0.17%	-0.11%	-0.01%	-0.01%	0.11%	0.28%	-0.21%	-0.10%	0.01%	0.19%	0.17%	0.38%
	(-1.29)	(-1.14)	(-0.07)	(-0.07)	(0.79)	(1.56)	(-1.06)	(-0.78)	(0.08)	(0.77)	(0.94)	(1.22)
5	-0.19%	-0.08%	-0.07%	0.07%	0.02%	0.22%	-0.47%	-0.18%	-0.19%	-0.02%	0.15%	0.62%
	(-1.22)	(-0.55)	(-0.46)	(0.41)	(0.1)	(1.18)	(-2.37)	(-1.38)	(-1.19)	(-0.11)	(0.68)	(3.03)***
(5-1)	0.19%	0.00%	-0.08%	0.11%	0.18%	0.00%	0.14%	-0.14%	-0.17%	0.02%	0.32%	0.18%
	(0.67)	(0)	(-0.39)	(0.55)	(0.74)	(0)	(0.43)	(-0.45)	(-0.67)	(0.06)	(1.36)	(0.62)

Value-weighted

Active share quintiles			EFIT quintiles						EFIT quintiles			
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
			FF4 alpha						FF5 alpha			
1	-0.85%	-0.37%	-0.38%	-0.28%	-0.38%	0.47%	-1.03%	-0.21%	-0.19%	-0.38%	-0.25%	0.78%
	(-3.44)	(-1.65)	(-1.94)	(-2.8)	(-2.49)	(1.41)	(-3.04)	(-0.69)	(-0.54)	(-3.16)	(-1.34)	(1.72)*
2	-0.62%	-0.40%	-0.65%	-0.45%	-0.35%	0.27%	-0.54%	-0.29%	-0.41%	-0.31%	-0.29%	0.25%
	(-3.64)	(-1.84)	(-4.93)	(-3.27)	(-2.55)	(1.68)*	(-3.76)	(-1.34)	(-2.31)	(-1.91)	(-2.1)	(1.97)*
3	-0.51%	-0.54%	-0.57%	-0.17%	-0.19%	0.32%	-0.58%	-0.67%	-0.67%	-0.08%	-0.06%	0.53%
	(-3.13)	(-3.5)	(-4.44)	(-1.34)	(-0.99)	(1.8)*	(-3.59)	(-4.49)	(-4.66)	(-0.52)	(-0.21)	(1.84)*
4	-0.50%	-0.24%	-0.22%	-0.26%	-0.23%	0.27%	-0.53%	-0.27%	-0.23%	-0.08%	-0.23%	0.30%
	(-4.55)	(-2.03)	(-2.06)	(-1.48)	(-1.74)	(1.52)	(-2.44)	(-2.02)	(-2.3)	(-0.33)	(-1.46)	(0.91)
5	-0.41%	-0.20%	-0.04%	-0.04%	-0.09%	0.31%	-0.68%	-0.34%	-0.22%	-0.12%	0.08%	0.76%
	(-2.16)	(-1.36)	(-0.24)	(-0.22)	(-0.36)	(2.02)**	(-3.14)	(-2.54)	(-1.19)	(-0.66)	(0.27)	(3.54)***
(5-1)	0.44%	0.17%	0.34%	0.25%	0.28%	-0.16%	0.36%	-0.13%	-0.03%	0.26%	0.33%	-0.03%
	(1.2)	(0.56)	(1.93)*	(1.66)*	(1.47)	(-0.5)	(0.84)	(-0.36)	(-0.1)	(1.08)	(1.84)*	(-0.08)

To check the robustness of the return predictability of EFIT, in Table 6-12, I sort funds into 25 portfolios based on EFIT and active skills. Consistent with my previous analysis in Table 6-12, in the double sorts of industry concentration index, reliance on public information, fund diversification, EFIT remains a significant predictor, while these active investment factors show relatively less predictive power on fund performance. This indicates that the return predictability of EFIT is not largely affected by these active investment factors. However, in the double sorts of return gap and active share, the alphas of the return spreads of them remain significant, especially for return gaps. While the return spreads of EFIT are insignificant in most quintiles.

More specifically, the results suggest that the return spread of EFIT still have some significance in predictability in the second quintile of the industry concentration index with an equal-weight FF5 alpha of 0.55% (t=2.15) or a value-weighted FF5 alpha of 0.66 (t=2.14). In addition, expected flow-induced trade shows a value-weighted FF5 alpha of 0.75% (t=2.41) in the third quintile of reliance on public information and an equal-weighted FF5 alpha 0.53% (t=1.81) in the fifth quintile of fund diversification.

In addition, consistent with my finding in Table 6-9, return gap and active share may partially explain the performance predictability of FIT. Expected Flow-induced trade shows lower significance compared to return spread from return gap and active share. The long-short spread of return gap has a value-weighted FF5 alpha ranging from 0.58 (t=2.7) to 2.06% (t=2.78), while return spread of active share has a value-weighted FF5 alpha of 0.33% (t=1.84) or a four-factor alpha of 0.34% (t=1.93). It implies that the predictability of expected flow-induced trade might be partially explained by return gaps and active shares. The skill of fund managers to cover hidden costs while accommodating flows or other transaction costs (Kacperczyk, Sialm and Zheng, 2008) and the ability to have alternative investment ideas with more capital inflows (Cremers and Petajisto, 2009) both contribute to the performance predictability of the flow-induced trading mechanism.

6.6 Conclusion

In this study, I analyze how fund managers trade when experiencing money inflows and outflows and its impact on fund portfolios and fund performance. Following previous studies by Lou (2012), Coval and Stafford (2007) and Anton and Polk (2014), this study extends flow-induced trading analysis to the emerging market of China. It also seeks to give a flow-based explanation to the abnormal returns of stocks held by multiple funds and to the relation between active management skills and stock return anomalies.

Utilizing a comprehensive mutual fund holding database, I systematically examine the flow-induced trading mechanism in China. Consistent with the US findings by Lou (2012), the flow-induced trading mechanism also exists in China. My results demonstrate that, first, flow-induced trading can positively predict stock returns and short-term fund performance. A long-short stock portfolio sorted by flow-induced trading can provide an annualized value-weighted four-factor alpha of 4.2% (t=2.7) in the first year after the formation quarter, and a long-short fund portfolio based on FIT can generate an annualized value-weighted four-factor alpha of 10.62% in a 3-month holding period. Second, it shows that anomaly returns exist in China. Especially, a long-short strategy based on the overall mispricing metric offers a value-weighted four-factor alpha of 2.412% (t= 8.38) monthly over a 3-month horizon. Given that stock return anomalies exist, skilled fund managers with higher return gap, higher industry concentration, greater diversification appear to trade on composite signals based on stock return anomalies, especially in the overall mispricing metric, non-investment anomalies, and active funds appear to exploit prior to 1997 anomalies. Third, active investment skills, including return gap and active share, might partially explain the short-term performance predictability of flow-induced trade. The findings also demonstrate the importance of using flow-induced trade and active investment factor as two dimensions to identify superior active funds.

Investors should be aware of the increasing tendency whereby skilled active funds buying holdings stocks may be a predictor of fund performance. Consistent with the US findings by Lou (2012), the developing market of China further confirms the impact of flow-induced patterns on stock returns and fund performance. Notably, this study sheds light on the value of active management in the mutual fund industry. Active managers may possess skills to reward their investors by exploiting stock return anomalies. Future works could incorporate a wide range of anomalies to study the flow-induced trade mechanism.

Chapter 7 Conclusion

7.1 Introduction

Mutual funds are an essential investment channel for investors in the modern world. The evolving literature describes various and mixed methods to identify superior management skills and fund outperformance. This thesis identifies three key empirical issues based on the following literature.

In the first place, earlier literature widely explores the decision mechanisms of mutual fund investors. Studies discover the flow determinants of fundamental fund characteristics, including lagged fund flow (Gruber,1996; Zheng, 1999), search costs (Sirri and Tufano, 1998), fund size (Chen et al., 2004), fund fees (Barber, Odean and Zheng, 2005), participation costs (Huang, Wei and Yan, 2007) and star ratings (Del Guercio and Tkac, 2008). In addition, scholars find evidence that active measures computed from fund holdings can reflect superior management ability, such as characteristic-based benchmarks (Daniel et al., 1997), industry concentration index (Kacperczyk, Sialm and Zheng, 2005), return gaps (Kacperczyk, Sialm and Zheng, 2008), reliance on public information (Kacperczyk and Seru, 2007) and active shares (Cremers and Petajisto, 2009). Moreover, the development of asset pricing models also provides investors with insights to compute the cost of their capital, such as the CAPM alpha (Jensen, 1968), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart model (Carhart, 1993), the Q-factor model (Hou, Xue and Zhang, 2014), the Fama-French five-factor model (Fama and French, 2015) and the mispricing-factor model (Stambaugh and Yuan, 2016).

Sophisticated investors may consider all the factors that explain the cross-sectional variations in fund performance (Grinblatt and Titman, 1989; Pástor and Stambaugh, 2002; Baber, Huang and Odean, 2016). It is essential to understand the priorities and relative importance attached in the decision mechanisms of investors in their fund selection. Mutual fund flows also allow us to know whether an asset pricing model successfully prices the risk in fund performance or if investors utilize other non-risk factors to evaluate fund performance (Berk and Van Binsbergen, 2016). However, the existing literature provides little evidence on how investors weigh different factors to evaluate funds, and investor preferences remain largely unexplored. Thus, the relative importance of fund flow determinants is a critical research gap to be examined.

As the largest emerging market, the Chinese mutual fund industry size has experienced massive growth in recent decades. It grew from 2.62 billion yuan in 2002 to 274.73 billion yuan in 2016. The active fund market in China has performed well with an average industry return of 8% in the last decade. Investor sophistication also differs largely from the US market, which enables us to robustly test the relative importance of flow determinants. Motivated by the literature and institutional backgrounds, I examine the relative importance of fund flow determinants from the perspective of risk and non-risk factors in both the China and US markets.

Second, as the decision mechanism of mutual fund investors is discovered, fund managers can adopt corresponding strategies to accommodate money inflows and outflows. Naturally, they have to deal with liquidity management on cash holdings. Simutin (2013) finds that fund managers holding more abnormal cash can outperform their peers with less abnormal cash by over 2% annually. They argue that fund managers with extra cash can purchase new stocks with good market timing, accommodate outflows or cover other costs. Graef et al. (2018) also find that abnormal cash holdings have predictive power for fund performance in the EU market. A long-short strategy based on abnormal cash offers a four-factor alpha of 0.48% in the subsequent six months. They document that fee structures, lagged fund flows, flow volatility and investment strategies mainly determine funds' cash holdings. Motivated by the literature, I test how fund managers determine their cash holdings and whether abnormal cash holdings predict returns with interactions of the smart money effect in the China and US markets. In addition, the literature documents that fund managers can utilize market beta as implicit leverage since mutual funds have constraints in taking leverage (Boguth and Simutin, 2018); higher liquidity beta funds tend to outperform their peers (Dong, Feng and Sadka, 2017). I further explore how cash holdings are related to investment strategies to fund risk exposures and whether abnormal cash holdings are a critical criterion for investors in the China and US markets.

Third, mutual fund flows offer profitable trading patterns for investors. Coval and Stafford (2007) find that investors can earn positive premiums by trading against mutual funds to provide liquidity. Also, Lou (2012) finds that flow-induced trading positively predicts fund performance and explains the smart money effect and performance persistence. Further investigation of flow-induced patterns in China may confirm the robustness of the US evidence. In addition, the active skills of fund manager have been well documented in the literature, including fund diversification (Pollet and Wilson, 2008), active share (Cremers and Petajisto, 2009) and return gap (Kacperczyk, Sialm and Zheng, 2008). However, Akbas et al. (2015) find that aggregate mutual fund flows appear to be dumb, while aggregate hedge fund flows appear to be smart. Also, the relation between individual fund-level flows and stock return anomalies has not been widely studied by prior literature. Motivated by the literature above, I systematically examine the flow-induced patterns of active funds and their relation to asset pricing anomalies on the individual fund level, rather than on the aggregate level.

In this thesis, I introduce the whole study in Chapter 1 and review relevant literature in Chapter 2. Then, I provide the institutional backgrounds of the China and US markets in Chapter 3. I examine the relative importance of flow determinants in China and the US in Chapter 4 and study the performance implications of decomposed R-squared in the US market. Furthermore, I study the determinants of cash holdings and examine the impact of abnormal cash holdings on fund investment strategies, fund flows and fund performance in the China and US markets in Chapter 5. Finally, I investigate the performance predictability of flow-induced trading in China and explore its relation to asset pricing anomalies in Chapter 6. The findings of this thesis have important implications for industry development in both the China and US markets. This chapter presents the conclusions drawn from the findings arrived in my study.

7.2 Main Findings

7.2.1 Different Industry Backgrounds Between China and the US

By manually collecting annual statistics from the mutual fund industry reports of China and the US, I find that market structure and investor sophistication differ from the perspectives described in Chapter 3, which motivates this comparative study between China and the US.

For industry characteristics, first, I find that the China mutual fund market has a relatively shorter history and smaller size than the US market. In recent years, since the financial crisis of 2008, both markets have had a steady asset growth in the equity fund sector. Second, active funds, including allocation funds and equity funds in China, on average, have provided a total return over 8% in the last decade, while US active funds, on average, have offered a positive return close to zero. Since investors seem to be more sophisticated and able to identify superior fund managers in a relative underperforming market (Gruber, 1996; Barber, Huang and Odean, 2016), it suggests that the smart money effect might be more pronounced in the US market.

For investor characteristics, first, individual participants account for the majority of investors in China (over 80%). It has been documented that individual investors who trade more may earn less, and overconfidence motivates their frequent trading (Barber and Odean, 2000). The purchasing behaviour of individual investors also induces smart money effects (Keswani and Stolin, 2008). This investor structure allows us to further confirm the robustness of my flow determinants analysis. Second, mutual fund investors in China are relatively younger and have modest incomes compared to investors in the US. Relatively wealthier investors might use advanced benchmarks in their fund picking (Barber, Huang and Odean, 2016). Different investor profiles allow us to further examine the robustness of investors' decision criteria studied by prior literature. Third, mutual fund investors in China tend more to purchase funds from banks and brokers (about 50%), while US investors have a relatively lower portion (about 39%) utilizing fund supermarkets and brokers. The literature documents that sophisticated investors utilize more direct-sold channels rather than broker-sold channels, and they rely more on advantageous information, rather than publicly available information (Bergstresser, Chalmers and Tufano, 2009; Chrisoffersen, Evans and Musto, 2013; Gucercio and Reuter, 2013). The different information supply from sales institutions also adds value to the comparative study between the US and China. Finally, investors have more speculative purposes in fund investments in China than investors in the US. The literature finds that investors have the ability to identify superior funds (Gruber, 1996); return-chasing investors give fund managers more incentives to take risk (Karceski, 2002). Speculative hedge fund flows tend to be smart at correcting stock mispricing, while mutual fund flows exacerbate stock return anomalies (Akbas et al., 2015). Sophisticated investors are more sensitive to exotic risk exposure (Agarwal, Green and Ren, 2018). The different investment purposes enhance our understanding of investor preferences in the China and US markets.

In sum, regarding both industry characteristics and investor profiles, the China fund market is a worthwhile place to investigate the decision mechanisms of mutual fund investors. A comparative study of China and the US can confirm the robustness of existing findings and enrich our understanding of the mutual fund market.

7.2.2 Asset Pricing Tests in China

The CAPM is dominant in modeling mutual fund flows than other risk models in the US market (Berk and Van Binsbergen, 2016; Barber, Huang and Odean, 2016). In Chapter 4, to test its validity in China, I conduct an asset pricing test from Berk and Van Binsbergen (2016) and find that the CAPM also outperforms other risk and "no risk" models in China. CAPM alpha has the highest correspondence with fund flows over 3-month to 4-year horizons. Among multiple risk models, the Fama-French three-factor model outperforms others over a 6-month horizon, while the Q-factor model outperforms other multiple risk models from 1-5 years. Among "no risk" models, excess market return has the best overall performance. First, it implies that investors do adjust risk difference in their investments. Second, systematic risk (beta) is the primary source of risk that investors consider. Third, the Fama-French factor models are industry standards to adjust risks in modelling fund flows in the short term (within six months), while investors may use the Q-factor model in the long term (over one-year). Furthermore, I employ an asset pricing test from Barber, Huang and Odean (2016). The results also confirm that CAPM shows the best ability to direct fund flows across risk models. In addition, investors adjust traditional risks like size factor and value factor in their fund decisions. The findings contribute to our understanding of asset pricing models as the CAPM also outperforms sophisticated risk models in the developing market with a different level of sophistication.

7.2.3 Relative Importance of Fund Flow Determinants in China

The success of the CAPM indicates that fund flows, partially driven by risk factors and performance, might also be explained by non-risk factors (Berk and Van Binsbergen, 2016). In Chapter 4, to analyze the role of non-risk factors in fund flows, I use the Shapley-Owen R-squared decomposition to study the relative importance of flow determinants in China. I classify flow determinants into four groups including risk-adjusted performance, risk beta, fundamental fund characteristics and active skill measures. The results suggest that non-risk factors, especially lagged flow and fund size from the fundamental fund characteristic group, play an essential role in directing fund flows in China. Specifically, lagged flow and fund size make higher contributions of 41.95% and 21.51% than CAPM alpha at 10.71%. The findings suggest that scale-decreasing returns (Chen et al., 2004; Pástor, Stambaugh and Taylor, 2015) and the smart money effect (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008) play important roles in determining fund flows. To test the robustness of the findings, I examine the explanatory power of these determinants in the long term from 1-3 years. The result suggests that risk factors and active skill measures' impact on fund flows is short-lived, while fundamental fund characteristics appear to affect fund flows persistently. Fund size has increasing explanatory power for fund flows, but active measure and lagged flow experience decreasing trends in explaining fund flows. Overall, the non-risk group still offers the highest explanatory power for fund flows. Furthermore, regressions with an interaction term between CAPM alpha and non-risk factors show that fund diversification and return gap may contribute to the success of CAPM in driving fund flows, while past volatility may have a negative effect on its success. Overall, the findings contribute to the existing literature studying flow determinants (Sirri and Tufano, 1998; Huang, Wei and Yan, 2007), scholars should know the priority and relative importance of these determinants for investors.

7.2.4 Relative Importance of Fund Flow Determinants in the US

To understand the decision mechanisms of US investors, I conduct multiple regression analyses and compute the decomposed R-squared of flow determinants in Chapter 4. First, I find that risk factors play a limited role in explaining fund flows. Systematic risk (CAPM) and three-factor risk (FF3) contribute 0.61% and 1.09% to the overall explanatory power of fund flows. Second, CAPM alpha offers a large explanatory power (10.33%) to fund flows. It might indicate that investors tend to use alpha rather than beta to pick funds. Third, fundamental fund characteristics offer the highest explanatory power to fund flows, ranging from 89.06% to 91.29%. Among all flow determinants, lagged fund flow has the highest explanatory power, ranging from 45.35%

to 47.02%. Fund size is the second most important determinant, ranging from 14.52% to 15.02%, while Morningstar rating is the third highest determinant ranging from 15.18% to 16.26%. Non-risk factors outperform risk factors and risk-adjusted returns in explaining fund flows in the US. Further investigation shows that lagged fund flows contribute to the success of CAPM in attracting fund flows, while fund size has a negative effect on it. The main results are robust under further tests from the perspectives of investor sophistication, scale-decreasing returns and participation costs. The findings contribute to understanding investors' decision mechanisms in the US market. Sophisticated investors should utilize all factors, whether priced or unpriced, to judge fund performance (Barber, Huang and Odean, 2016). Consistent with the findings in the China market, they place relatively greater weight on non-risk factors than risk factors, especially fund size and lagged fund flow (Berk and Van Binsbergen, 2016).

7.2.5 Smart-to-Dumb Ratio to Identify Smart Money in the US

To examine the performance implications of decomposed-R-squared and identify smart investors investing using sophisticated benchmarks, I propose the Smart-to-Dumb Ratio (SDR) based on the relative importance of flow determinants. The literature documents that the persistence of mutual fund performance varies across time (Brown and Goetzmann, 1995), it exists in the short term (Bollen and Busse, 2005), and performance chasers seem to be unsophisticated (Karceski, 2002). While fundamental fund characteristics such as fund size, fund fee and lagged flow are well documented as affecting fund flows (Chen et al., 2004; Pollet and Wilson, 2008; Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008; Barber, Odean and Zheng, 2005; Huang, Wei and Yan, 2007). Building on the literature and evidence in the US market, I hypothesize that the investors who trade on fundamental fund characteristics are relatively smarter than investors who evaluate funds based on past performance in the US.

I construct a novel proxy, Smart-to-Dumb Ratio (SDR), which takes the decomposed R-squared of fundamental fund characteristics divided by decomposed R-squared of past performance. I further study the performance predictability of SDR. I sort funds into deciles based on their SDR, and then I construct a hedge portfolio by longing funds with high SDRs and shorting funds with low SDRs. The long-short hedge portfolio generates an annualized four-factor alpha ranging from 85.08 (t=3.94) basis points of an equal-weighted portfolio to 121.8 (t=2.33) basis points of a value-weighted portfolio, computed based on net returns in a 6-month holding period. The findings are consistent with Barber, Huang and Odean (2016) as sophisticated investors may utilize advanced benchmarks based on all factors, whether priced or unpriced, to identify well-performing funds. Further robustness tests show that SDR indicates superior fund family skills, high SDR funds rely less on public information from prime brokers, and funds with high SDR may be able to exploit the stock return anomalies.

It offers the new performance predictor, SDR, from the perspective of the smart money of sophisticated investors. The findings contribute to the existing literature on the smart money effect (Gruber, 1996; Zheng, 1999; Keswani and Stolin, 2008). Baed on SDR, investors have an empirical metric to identify the smart money, which is predictive of superior fund performance. It also contributes to the existing literature on predicting fund performance (Kacpercyzyk, Sialm and Zheng, 2005; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013).

7.2.6 Determinants of Cash Holdings in China and the US

Holding cash is costly in terms of investment opportunities (Wermers, 2000), while it also provides fund managers with flexibility to maintain liquidity through satisfying outflows, accommodating uncertain inflows, or controlling for other transaction costs (Chordia, 1996; Simutin, 2013). In Chapter 5, I test the hypothesis that the factors affecting fund managers in China and the US to determine cash levels differ, given that the market structures and investor profiles are different. I conduct multiple regressions and use Shapley-Owen R-squared decomposition to analyze the determinants of cash holdings. The results show that fund managers in China are more affected by non-risk factors than risk factors to determine their cash holdings, while US fund managers are more influenced by risk factors than non-risk factors. In China, small and young funds with higher past return volatility, lower report attention and lower active shares hold more cash. Fund size, fund age, return volatility, fund-report attention and active share respectively explain 14.39%, 14.62%, 19.66%, 15.56% and 4.18% of cash holdings in the future quarter. In addition, funds with the lower market beta, higher lagged flows and larger fund families tend to hold more cash in the US. Market beta, lagged fund flow and family size account for 43.08%, 11.29% and 14.21% of cash holdings in the next quarter. The findings extend our knowledge of the factors affecting fund managers in determining their cash levels to main liquidity (Chardia, 1996; Wermers, 2000; Simutin, 2013).

7.2.7 Abnormal Cash Holdings and Fund Behaviour in China and the US

To further explore the investment strategies of skilled fund managers in liquidity management, I examine the investment strategies of fund managers with superior skills in cash management. The results show that US funds tend to reduce their portfolio risk exposure to market risk, momentum risk, profitability risk, management risk and performance risk, while China funds tend to tilt their portfolios to increase their exposure to asset growth and profitability risk. The findings suggest that US managers with high abnormal cash holdings might be more sensitive to risk and reduce the risk exposure of their portfolios, while managers in China are more aggressive to profit from asset growth and profitability risk.

I further study the relation between abnormal cash holdings and fund flows. The results show that abnormal cash holdings drive future fund flows in both China and US markets. 1% of abnormal cash holding (ACH) is significantly related to 0.162% (t=2.435) of fund inflows in China or 0.183% (t=2.959) of fund inflows in the US. In addition, as Simutin (2013) finds that abnormal cash holdings can predict better fund performance, I further examine the performance predictability of abnormal cash holdings. By constructing fund portfolios sorted by abnormal cash holdings, I find that funds with higher abnormal cash holdings tend to outperform their peers with low abnormal cash in the US market (Simutin, 2013; Graef et al., 2018). A strategy by longing high ACH funds and shorting low ACH funds generates a monthly three-factor alpha of 0.065% (t=2.02) and a monthly four-factor alpha of 0.06% (t=1.85). Also, the smart money effect might have a positive impact on abnormal cash holdings in predicting fund performance in the US. US funds with higher abnormal cash appear to outperform their peers under the medium flow level. This indicates that sophisticated investors may take advantage of abnormal cash holdings in their fund selection. The findings contribute to our knowledge of liquidity management in both developed and developing markets.

7.2.8 Flow-Induced Trade and Stock Performance

Flow-induced trading patterns have been recognized as positively predicting the stock and fund performance by Lou (2012). With a comprehensive mutual funds holdings database, I investigate flow-induced patterns in the China market in Chapter 6. Consistent with the US findings by Lou (2012), the flow-induced trading mechanism also exists in China. Specifically, I find that flow-induced trade is positively associated with future stock returns. The long-short stock portfolio sorted by flow-induced trade generates an annualized value-weighted four-factor alpha of 4.2% over a 1-year horizon. The flow-induced pattern persistently drives up the stock price for two years with a little reversal. In addition, the predictability of flow-induced trade is more pronounced in a short-term period of three months. The results confirm the findings by Lou (2012) and provide profitable and tradable strategies for institutional investors.

7.2.9 Flow-Induced Trade and Stock Return Anomalies

To examine whether mutual funds are smart and whether skilled fund managers can trade on stock return anomalies when experiencing money inflows or outflows, I study the relation between flow-induced trade and stock return anomalies. First, I systematically examine the returns of anomalies and their composites by Stambaugh, Yu and Yuan (2012). A long-short strategy based on overall mispricing metric generates a monthly value-weighted four-factor alpha of 2.412% (t= 8.38) over a 3-month horizon. In addition, individual anomalies, including total accruals, gross profitability, asset growth, return on assets, net stock issues and momentum, show positive and significant alphas of return spreads over 3-month to 12-month horizons. Moreover, composite anomalies, including non-investment anomalies, investment anomalies, three anomalies documented prior to 1997 and six anomalies from 1997 forward, also exhibit positive and significant alphas of return spreads over 3-month to 12-month horizons. This analysis sheds light on the empirical evidence of these profitable anomalies in China. Institutional investors may recognize these anomalies and implement arbitrage strategies to obtain high premiums.

Second, I find that skilled fund managers appear to exploit the overall mispricing metric based on the nine anomalies studied by Stambaugh, Yu and Yuan (2012). More specifically, fund managers with a high return gap, concentrated industry investments and large diversification may trade in the composite signals of non-investment anomalies, including return on assets, gross profitability, net stock issues total accruals and momentum. Also, active funds appear to exploit the composite signals of prior to 1997 anomalies, including net stock issues, momentum and total accruals. The findings contribute to the studies on active management (Kacperczyk and Seru, 2007; Pollet and Wilson 2008, Cremers and Petajisto, 2009), they support that the skills of active fund managers do add values by exploiting asset-pricing anomalies. They also contribute to our understanding of the consequences of smart money. Fund performance can be evaluated with a two-dimensional view of both sophisticated investors and skilled fund managers.

7.2.10 Flow-Induced Trade and Fund Performance

As Lou (2012) finds that flow-induced trade also predicts fund performance, I further extend my analysis from the stock level to the individual fund level. I find that the predictability of flow-induced trade exists in the short-term horizon of three months. A long-short fund portfolio based on FIT produces an annualized value-weighted four-factor alpha of 10.62%. Also, I further study the source of its predictability. By double sorting funds by flow-induced trade and active investment factors, I find that the predictability of flow-induced trade might be partially explained by return gap and active share. Furthermore, I seek to utilize predictable flows to construct flow-induced trade. The results are robust as the expected flow-induced trade also persistently and positively predicts fund performance. Funds with expected flow-induced purchases significantly outperform funds with expected flow-induced selling. The findings contribute to the studies on institutional price pressure (Coval and Stafford, 2008; Lou, 2012). This also implies that a flow-induced pattern on funds also exists in the developing market of China, so there is a tradable pattern that is profitable for institutional investors.

7.3 Limitations and Directions for Future Research

Several constraints limit this research, and future studies could systematically explore them to enhance our understanding of mutual funds. First, due to the data availability of US mutual fund holdings, this study has not constructed active skill predictors to study their impact in the US market. Future studies could explore the results with full controls for other active skill measures constructed by portfolio holdings data in the US market. Second, while there is detailed investor sophistication data for the US market, it is not possible to obtain their equivalent for the China mutual fund market. In addition, historical Morningstar rating data in China are not sufficient to cover all funds in the sample period. Future research could explore how different levels of sophistication affects investors' decision mechanisms in China using sophistication settings from the US analysis. Third, for the performance and application of the Smart-to-Dumb Ratio, the observation and time length of the sample limits its application in China. With more observations in later years, the performance predictability of SDR could also be examined in China. Fourth, I focus on actively managed funds in both the China and US markets. The analysis could be considerably extended to international fund markets. Finally, there has been a growing number of ETF funds in recent decades. How do passive funds affect investor preferences? The impact of passive funds on investor preferences could be examined in future studies.

Bibliography

Agarwal, V., Gay, G.D. and Ling, L. 2014. Window dressing in mutual funds. *Review of Financial Studies*. **27**(11), pp.3133-3170.

Agarwal, V., Green, T.C. and Ren, H. 2018. Alpha or beta in the eye of the beholder: What drives hedge fund flows?. *Journal of Financial Economics*. **127**(3), pp.417-434.

Akbas, F., Armstrong, W.J., Sorescu, S. and Subrahmanyam, A. 2015. Smart money, dumb money, and capital market anomalies. *Journal of Financial Economics*. **118**(2), pp.355-382.

Akbas, F., Armstrong, W.J., Sorescu, S. and Subrahmanyam, A. 2016. Capital market efficiency and arbitrage efficacy. *Journal of Financial and Quantitative Analysis*. **51**(2), pp.387-413.

Amihud, Y. and Goyenko, R. 2013. Mutual fund's R^2 as predictor of performance. *Review of Financial Studies*. **26**(3), pp.667-694.

Andonov, A., Bauer, R.M. and Cremers, K.J. 2017. Pension fund asset allocation and liability discount rates. *Review of Financial Studies*. **30**(8), pp.2555-2595.

Anton, M. and Polk, C. 2014. Connected stocks. *Journal of Finance*. **69**(3), pp.1099-1127.

Arif, S., Ben-Rephael, A. and Lee, C. 2015. *Do short-sellers profit from mutual funds? Evidence from daily trades*. Rock Center for Corporate Governance at Stanford University Working Paper No.3427. [Online]. [Accessed 1 January 2018]. Available from: https://www.gsb.stanford.edu/faculty-research/working-papers/do-short-sellers-profit-mutual-funds-evidence-daily-trades

Armstrong, W.J., Genc, E. and Verbeek, M. 2017. [Forthcoming]. Going for Gold: An Analysis of Morningstar Analyst Ratings. *Management Science*. [Online]. [Accessed 1 February 2018]. Available from: https://doi.org/10.1287/mnsc.2017.2884

Asset Management Associate of China. 2012-2016. *China Securities Investment Fund Fact Book 2012-2016*. [Online]. Beijing: China Financial & Economic Publishing House. [Accessed 1 January 2018]. Available from: http://www.amac.org.cn/

Asset Management Association of China. 2009-2014. *The Survey Report of Fund Investors 2010-2014*. [Online]. [Accessed 1 January 2018]. Available from: http://www.amac.org.cn/

Bai, J.J., Ma, L., Mullally, K.A. and Solomon, D.H. 2018. What a difference a (birth) month makes: The relative age effect and fund manager performance. *Journal of Financial Economics*. **132**(1), pp.200-221.

Baker, M., Bradley, B. and Wurgler, J. 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal*. **67**(1), pp.40-54.

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

Barber, B.M., Huang, X. and Odean, T. 2016. Which factors matter to investors? Evidence from mutual fund flows. *Review of Financial Studies*. **29**(10), pp.2600-2642.

Barber, B.M., Odean, T. and Zheng, L. 2005. Out of sight, out of mind: The effects of expenses on mutual fund flows. *Journal of Business*. **78**(6), pp.2095-2120.

Bär, M., Kempf, A. and Ruenzi, S. 2010. Is a team different from the sum of its parts? Evidence from mutual fund managers. *Review of Finance*. **15**(2), 359-396.

Ben-Rephael, A., Kandel, S. and Wohl, A. 2012. Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics*. **104**(2), pp.363-382.

Bergstresser, D., Chalmers, J.M. and Tufano, P. 2008. Assessing the costs and benefits of brokers in the mutual fund industry. *Review of Financial Studies*. **22**(10), pp.4129-4156.

Berk, J.B. and Green, R.C. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy*. **112**(6), pp.1269-1295.

Berk, J.B. and Van Binsbergen, J.H. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics*. **118**(1), pp.1-20.

Berk, J.B. and Van Binsbergen, J.H. 2016. Assessing asset pricing models using revealed preference. *Journal of Financial Economics*. **119**(1), pp.1-23.

Bhojraj, S., Cho, Y.J. and Yehuda, N. 2012. Mutual fund family size and mutual fund performance: The role of regulatory changes. *Journal of Accounting Research*. **50**(3), pp.647-684.

Boguth, O. and Simutin, M. 2018. Leverage constraints and asset prices: Insights from mutual fund risk taking. *Journal of Financial Economics*. **127**(2), pp.325-341.

Bollen, N.P. and Busse, J.A. 2005. Short-term persistence in mutual fund performance. *Review of Financial Studies*. **18**(2), pp.569-597.

Brown, S.J. and Goetzmann, W.N. 1995. Performance persistence. *Journal of Finance*. **50**(2), pp.679-698.

Carhart, M.M. 1997. On persistence in mutual fund performance. *Journal of Finance*. **52**(1), pp.57-82.

Chen, L., Novy-Marx, R. and Zhang, L. 2011. *An Alternative Three-Factor Model*. Working paper. [Online]. [Accessed 1 January 2018]. Available from: https://ssrn.com/abstract=1418117

Chen, J., Hanson, S., Hong, H. and Stein, J.C. 2008. *Do Hedge Funds Profit from Mutual-Fund Distress?*. National Bureau of Economic Research Working Paper No. w13786. [Online]. [Accessed 1 January 2018]. Available from: https://www.nber.org/papers/w13786

Chen, J., Hong, H., Huang, M. and Kubik, J.D. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review*. **94**(5), pp.1276-1302.

Chernenko, S. and Sunderam, A. 2016. *Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds*. National Bureau of Economic Research Working Paper No. w22391. [Online]. [Accessed 1 January 2018]. Available from: https://www.nber.org/papers/w22391

Chevalier, J. and Ellison, G. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*. **105**(6), pp.1167-1200.

Chevan, A. and Sutherland, M. 1991. Hierarchical partitioning. *American Statistician*. **45**(2), pp.90-96.

China Security Regulatory Commission. 2007. *The History of Mutual Fund Development in China*. [Online]. [Accessed 1 January 2018]. Available from: http://www.csrc.gov.cn/pub/shanghai/xxfw/tzzsyd/zqcswd/200704/t20070411_74772.htm

Chiu, H.H. and Kini, O. 2013. Equity issuances, equity mutual fund flows, and noise trader sentiment. *Review of Finance*. **18**(2), pp.749-802.

Chordia, T. 1996. The structure of mutual fund charges. *Journal of Financial Economics*. **41**(1), pp.3-39.

Christoffersen, S.E., Evans, R. and Musto, D.K. 2013. What do consumers' fund flows maximize? Evidence from their brokers' incentives. *Journal of Finance*. **68**(1), pp.201-235.

Christoffersen, S.E. and Simutin, M. 2017. On the demand for high-beta stocks: Evidence from mutual funds. *Review of Financial Studies*. **30**(8), pp.2596-2620.

Chung, J.W. and Kang, B.U. 2016. Prime broker-level comovement in hedge fund returns: Information or contagion?. *Review of Financial Studies*. **29**(12), pp.3321-3353.

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

Coval, J. and Stafford, E. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*. **86**(2), pp.479-512.

Cremers, K.J.M. and Pareek, A. 2016. Patient capital outperformance: The investment skill of high active share managers who trade infrequently. *Journal of Financial Economics*. **122**(2), pp.288-306.

Cremers, K.J.M. and Petajisto, A. 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*. **22**(9), pp.3329-3365.

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

Daniel, K. and Titman, S. 2006. Market reactions to tangible and intangible information. *Journal of Finance*. **61**(4), pp.1605-1643.

Del Guercio, D. and Reuter, J. 2014. Mutual fund performance and the incentive to generate alpha. *Journal of Finance*. **69**(4), pp.1673-1704.

Del Guercio, D. and Tkac, P.A. 2008. Star power: The effect of Morningstar ratings on mutual fund flow. *Journal of Financial and Quantitative Analysis*. **43**(4), pp.907-936.

Devicienti, F. 2010. Shapley-value decompositions of changes in wage distributions: a note. *Journal of Economic Inequality*. **8**(1), pp.35-45.

Dittmar, A. and Mahrt-Smith, J. 2007. Corporate governance and the value of cash holdings. *Journal of Financial Economics*. **83**(3), pp.599-634.

Dong, X., Feng, S. and Sadka, R. 2017. [Forthcoming]. Liquidity risk and mutual fund performance. *Management Science*. [Online]. [Accessed 1 February 2018]. Available from: https://doi.org/10.1287/mnsc.2017.2851

Dyakov, T. and Verbeek, M. 2013. Front-running of mutual fund fire-sales. *Journal of Banking & Finance*. **37**(12), pp.4931-4942.

Edelen, R.M. 1999. Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics*. **53**(3), pp.439-466.

Edelen, R.M. and Warner, J.B. 2001. Aggregate price effects of institutional trading: A study of mutual fund flow and market returns. *Journal of Financial Economics*. **59**(2), pp.195-220.

Elton, E.J., Gruber, M.J. and Blake, C.R. 1996. The persistence of risk-adjusted mutual fund performance. *Journal of Business*. **69**(2), pp.133-157.

Elton, E.J., Gruber, M.J. and Blake, C.R. 2001. A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases. *Journal of Finance*. **56**(6), pp.2415-2430.

Fama, E.F. and French, K.R. 1992. The cross-section of expected stock returns. *Journal of Finance*. **47**(2), pp.427-465.

Fama, E.F. and French, K.R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*. **33**(1), pp.3-56.

Fama, E.F. and French, K.R. 2015. A five-factor asset pricing model. *Journal of Financial Economics*. **116**(1), pp.1-22.

Fama, E.F. and MacBeth, J.D. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*. **81**(3), pp.607-636.

Ferreira, M.A., Keswani, A., Miguel, A.F. and Ramos, S.B. 2013. The determinants of mutual fund performance: A cross-country study. *Review of Finance*. **17**(2), pp.483-525.

Ferson, W. and Mo, H. 2016. Performance measurement with selectivity, market and volatility timing. *Journal of Financial Economics*. **121**(1), pp.93-110.

Fortin, R., Michelson, S. and Jordan-Wagner, J. 1999. Does mutual fund manager tenure matter?. *Journal of Financial Planning*. **12**(7), pp.72-79.

Frazzini, A. and Lamont, O.A. 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*. **88**(2), pp.299-322.

Frazzini, A. and Pedersen, L.H. 2014. Betting against beta. *Journal of Financial Economics*. **111**(1), pp.1-25.

Franzoni, F. and Schmalz, M.C. 2017. Fund flows and market states. *Review of Financial Studies*. **30**(8), pp.2621-2673.

Fresard, L. 2010. Financial strength and product market behavior: The real effects of corporate cash holdings. *Journal of Finance*. **65**(3), pp.1097-1122.

Guo, X. 2016. *Mutual fund style volatility and fund flows*. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=2716255

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

Goldstein, I., Jiang, H. and Ng, D.T. 2017. Investor flows and fragility in corporate bond funds. *Journal of Financial Economics*. **126**(3), pp.592-613.

Graef, F., Vogt, P., Vonhoff, V. and Weigert, F. 2018. *Cash holdings and the performance of European mutual funds*. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=3125678

Greene, W.H. 2002. *Econometric analysis*. 5th ed. New Jersey: Prentice Hall.

Grinblatt, M. and Titman, S. 1989. Portfolio performance evaluation: Old issues and new insights. *Review of Financial Studies*. **2**(3), pp.393-421.

Grinblatt, M. and Titman, S. 1992. The persistence of mutual fund performance. *Journal of Finance*. **47**(5), pp.1977-1984.

Grinblatt, M. and Titman, S. 1993. Performance measurement without benchmarks: An examination of mutual fund returns. *Journal of Business*. **66**(1), pp.47-68.

Gruber, M.J. 1996. Another puzzle: The growth in actively managed mutual funds. *Journal of Finance*. **51**(3), pp.783-810.

Hanouna, P., Novak, J., Riley, T. and Stahel, C. 2015. *Liquidity and flows of US mutual funds*. Division of Economic and Risk Analysis White Paper, US Securities and Exchange Commission. [Online]. [Accessed 1 January 2018]. Available from: https://www.sec.gov/dera/staff-papers/white-papers/liquidity-white-paper-09-2015.html

Han, Y., Noe, T. and Rebello, M. 2017. Horses for courses: Fund managers and organizational structures. *Journal of Financial and Quantitative Analysis*. **52**(6), pp.2779-2807.

Harvey, C.R. and Liu, Y. 2017. *Decreasing returns to scale, fund flows, and performance*. Working paper. [Online]. [Accessed 1 February 2018]. Available from: https://ssrn.com/abstract=2990737

Hendricks, D., Patel, J. and Zeckhauser, R. 1993. Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988. *Journal of Finance*. **48**(1), pp.93-130.

Hirshleifer, D., Hou, K., Teoh, S. H. and Zhang, Y. 2004. Do investors overvalue firms with bloated balance sheets?. *Journal of Accounting and Economics*. **38**(1), pp.297-331.

Hou, K., Xue, C. and Zhang, L. 2015. Digesting anomalies: An investment approach. *Review of Financial Studies*. **28**(3), pp.650-705.

Huang, J., Wei, K. D. and Yan, H. 2004. *Volatility of performance and mutual fund flows*. Working paper. [Online]. [Accessed 1 February 2018]. Available from: https://www.researchgate.net/publication/228893380_Volatility_of_performance_and_mutual_fund_flows

Huang, J., Wei, K.D. and Yan, H. 2007. Participation costs and the sensitivity of fund flows to past performance. *Journal of Finance*. **62**(3), pp.1273-1311.

Huang, S., Lou, D. and Polk, C. 2016. *The booms and busts of beta arbitrage*. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=2843570

Hüttner, F. and Sunder, M. 2011. *Decomposing* R^2 *with the Owen value*. Faculty of Economics and Management Science, University of Leipzig Working Paper No.100. [Online]. [Accessed 1 February 2018]. Available from: https://www.econstor.eu/handle/10419/52301

Investment Company Institute. 2012-2017. *Investment Company Fact Book 2012-2017*. [Online]. [Accessed 1 January 2018]. Available from: https://www.ici.org/research/industry_research/fact_book

Ippolito, R.A. 1992. Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *Journal of Law and Economics*. **35**(1), pp.45-70.

Israeli, O. 2007. A Shapley-based decomposition of the R-square of a linear regression. *Journal of Economic Inequality*. **5**(2), pp.199-212.

Ivković, Z. and Weisbenner, S. 2009. Individual investor mutual fund flows. *Journal of Financial Economics*. **92**(2), pp.223-237.

Jain, P.C. and Wu, J.S. 2000. Truth in mutual fund advertising: Evidence on future performance and fund flows. *Journal of Finance*. **55**(2), pp.937-958.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*. **48**(1), pp.65-91.

Jenkinson, T., Jones, H. and Martinez, J.V. 2016. Picking winners? Investment consultants' recommendations of fund managers. *Journal of Finance*. **71**(5), pp.2333-2370.

Jensen, M.C. 1968. The performance of mutual funds in the period 1945–1964. *Journal of Finance*. **23**(2), pp.389-416.

Jiang, H. and Verardo, M. 2018. Does herding behavior reveal skill? An analysis of mutual fund performance. *Journal of Finance*. **73**(5), pp. 2229-2269.

Johnson, J.W. and LeBreton, J.M. 2004. History and use of relative importance indices in organizational research. *Organizational Research Methods*. **7**(3), pp.238-257.

Kacperczyk, M., Nieuwerburgh, S.V. and Veldkamp, L. 2014. Time-varying fund manager skill. *Journal of Finance*. **69**(4), pp.1455-1484.

Kacperczyk, M. and Seru, A. 2007. Fund manager use of public information: New evidence on managerial skills. *Journal of Finance*. **62**(2), pp.485-528.

Kacperczyk, M., Sialm, C. and Zheng, L. 2005. On the industry concentration of actively managed equity mutual funds. *Journal of Finance*. **60**(4), pp.1983-2011.

Kacperczyk, M., Sialm, C. and Zheng, L. 2008. Unobserved actions of mutual funds. *Review of Financial Studies*. **21**(6), pp.2379-2416.

Kaniel, R., Tompaidis, S. and Zhou, T. 2018. [Forthcoming]. Impact of managerial commitment on risk taking with dynamic fund flows. *Management Science*. [Online].

[Accessed 1 February 2018]. Available from: https://doi.org/10.1287/mnsc.2017.2946

Karceski, J. 2002. Returns-chasing behavior, mutual funds, and beta's death. *Journal of Financial and Quantitative Analysis*. **37**(4), pp.559-594.

Keswani, A. and Stolin, D. 2008. Which money is smart? Mutual fund buys and sells of individual and institutional investors. *Journal of Finance*. 63(1), pp.85-118.

Khorana, A., Servaes, H. and Wedge, L. 2007. Portfolio manager ownership and fund performance. *Journal of Financial Economics*. **85**(1), pp.179-204.

Loth, R. [no date]. *History of the mutual fund.* [Online]. [Accessed 1 February 2018]. Available from: https://www.investopedia.com/university/quality-mutual-fund/chp1-introduction/mf-history.asp

Lou, D. 2012. A flow-based explanation for return predictability. *Review of Financial Studies*. **25**(12), pp.3457-3489.

Lou, D. and Polk, C. 2013. *Comomentum: Inferring Arbitrage Activity from Return Correlations*. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=2023989

Loughran, T. and Ritter, J. R. 1995. The new issues puzzle. *Journal of Finance*. **50**(1), pp.23-51.

McWhinney, J. 2018. *A brief history of the mutual fund.* [Online]. [Accessed 1 February 2018]. Available from: https://www.investopedia.com/articles/mutualfund/05/mfhistory.asp

Nanda, V., Wang, Z.J. and Zheng, L. 2004. Family values and the star phenomenon: Strategies of mutual fund families. *Review of Financial Studies*. **17**(3), pp.667-698.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*. **55**(3), pp.703-708.

Novy-Marx, R. 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics*, **108**(1), pp.1-28.

Opler, T., Pinkowitz, L., Stulz, R. and Williamson, R. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics*. **52**(1), pp.3-46.

Pástor, Ľ. and Stambaugh, R.F. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy*. 111(3), pp.642-685.

Pástor, Ľ. and Stambaugh, R.F. 2012. On the size of the active management industry. *Journal of Political Economy*. **120**(4), pp.740-781.

Pástor, Ľ., Stambaugh, R.F. and Taylor, L.A. 2015. Scale and skill in active management. *Journal of Financial Economics*. **116**(1), pp.23-45.

Pástor, Ľ., Stambaugh, R.F. and Taylor, L.A. 2017. *Portfolio liquidity and diversification: Theory and evidence*. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=3016781

Pollet, J.M. and Wilson, M. 2008. How does size affect mutual fund behavior?. *Journal of Finance*. **63**(6), pp.2941-2969.

Ritter, J.R. 1991. The long-run performance of initial public offerings. *Journal of Finance*. **46**(1), pp.3-27.

Sapp, T. and Tiwari, A. 2004. Does stock return momentum explain the "smart money" effect?. *Journal of Finance*. **59**(6), pp.2605-2622.

Sastre, M. and Trannoy, A. 2002. Shapley inequality decomposition by factor components: Some methodological issues. *Journal of Economics*. **77**(1), pp.51-89.

Security Association of China. 2006. *Security Investment Funds*. Beijing: China Financial & Economic Publishing House.

Shapley, L.S. 1953. A value for n-person games. *Contributions to the Theory of Games*. **2**(28), pp.307-317.

Sharpe, W.F. 1966. Mutual fund performance. *Journal of Business*. **39**(1), pp.119-138.

Sheng, J., Simutin, M. and Zhang, T. 2017. Cheaper is Not Better: On the Superior Performance of High-Fee Mutual Funds. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=2912511

Shive, S. and Yun, H. 2013. Are mutual funds sitting ducks?. *Journal of Financial Economics*. **107**(1), pp.220-237.

Shorrocks, A.F. 2013. Decomposition procedures for distributional analysis: A unified framework based on the Shapley value. *Journal of Economic Inequality*. **11**(1), pp.99-126.

Simutin, M. 2013. Cash holdings and mutual fund performance. *Review of Finance*. **18**(4), pp.1425-1464.

Sirri E.R. and Peter Tufano. 1998. Costly search and mutual fund flows. *Journal of Finance*. **53**(5), pp.1589-1622.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings?. *Accounting Review*. **71**(3), pp.289-315.

Stambaugh, R.F., Yu, J. and Yuan, Y. 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*. **104**(2), pp.288-302.

Stambaugh, R.F., Yu, J. and Yuan, Y. 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*. **70**(5), pp.1903-1948.

Stambaugh, R.F. and Yuan, Y. 2016. Mispricing factors. *Review of Financial Studies*. **30**(4), pp.1270-1315.

Sun, Y. 2014. *The effect of index fund competition on money management fees*. Working paper. [Online]. [Accessed 1 January 2018]. Available from: https://ssrn.com/abstract=2432361

Titman, S., Wei, K. J. and Xie, F. 2004. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*. **39**(4), pp.677-700.

Warther, V.A. 1995. Aggregate mutual fund flows and security returns. *Journal of Financial Economics*. **39**(2-3), pp.209-235.

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

Wermers, R. 2003. Is money really 'smart'? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=414420

Wu, B. 2006. *The comparative analysis of the development of the security investment funds between China and the US*. Ph.D. thesis, Shanghai Academy of Social Science.

Yan, X.S. 2006. The determinants and implications of mutual fund cash holdings: Theory and evidence. *Financial Management*. **35**(2), pp.67-91.

Yan, X.S. 2008. Liquidity, investment style, and the relation between fund size and fund performance. *Journal of Financial and Quantitative Analysis*. **43**(3), pp.741-767.

Yin, C. 2016. The optimal size of hedge funds: Conflict between investors and fund managers. *Journal of Finance*. **71**(4), pp.1857-1894.

Yu, H.Y. 2012. Where are the smart investors? New evidence of the smart money effect. *Journal of Empirical Finance*. **19**(1), pp.51-64.

Zeng, Y. 2017. *A Dynamic Theory of Mutual Fund Runs and Liquidity Management*. Working paper. [Online]. [Accessed 1 March 2018]. Available from: https://ssrn.com/abstract=2907718

Zhang, Q., Cai, C.X. and Keasey, K. 2013. Market reaction to earnings news: A unified test of information risk and transaction costs. *Journal of Accounting and Economics*. **56**(2), pp.251-266.

Zheng, L. 1999. Is money smart? A study of mutual fund investors' fund selection ability. *Journal of Finance*. **54**(3), pp.901-933.