GALLA SALGANIK

Essays on Investment Flows of Hedge Fund and Mutual Fund Investors

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PROEFSCHRIFT

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PROMOTERS:	prof. dr. Jenke ter Horst dr. Paul Sengmueller
DEFENSE COMMITTEE MEMBERS:	prof. dr. Joost Driessen dr. Peter C. de Goeij prof. dr. Shmuel Hauser prof. dr. Luc Renneboog prof. dr. Frans de Roon

To my family and friends.

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Galla Salganik

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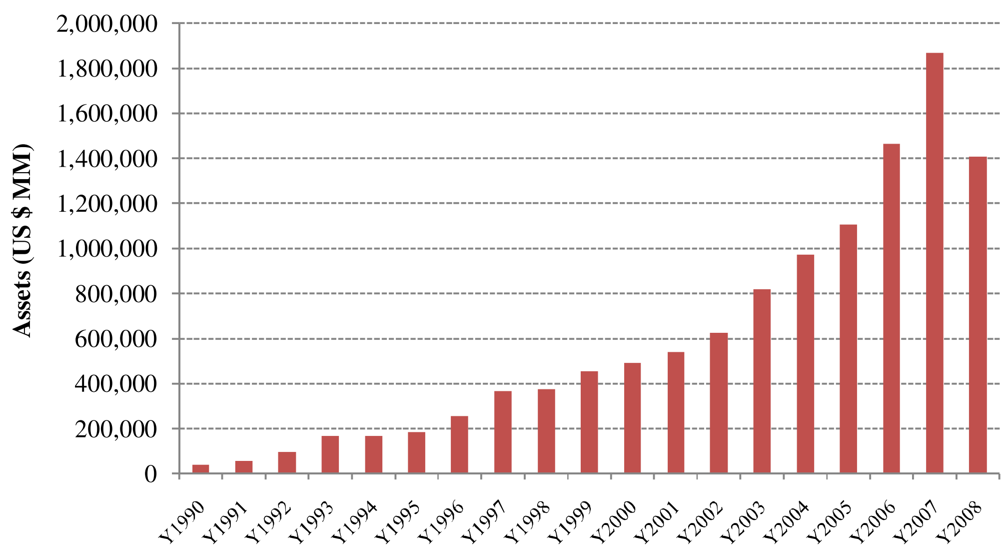
CHAPTER 1

Introduction

Providing actively managed portfolios in publicly traded assets, hedge funds and mutual funds have exactly the same economic function. In contrast to mutual funds – the most popular collective investment vehicles (Babalos, Kostacis, Philipas (2009)) managing a considerable part of financial assets worldwide[1] – the overall size of hedge funds is relatively small[2]. Nevertheless, experiencing tremendous growth over the past two decades (See Figure 1.1), the active role that hedge funds play in financial markets makes them much more important than suggested by their size alone (Garbaravicius, Dierick, 2005). In fact, hedge funds account for nearly half the trading on the New York and London stock exchanges (Stulz, 2007).

Figure 1.1

*Estimated Growth of Assets
Hedge Fund Industry 1990 – 2008



* Source: Hedge Fund Research database

Hedge funds differ from mutual funds by lack of regulations, by limited transparency and disclosure, and by their internal structure (see, e.g., Fung and Hsieh, 1997). Having a great deal of flexibility, hedge fund managers typically can invest in international and

[1] At year-end 2009 mutual funds assets worldwide counted for about $23 trillion, almost half of which belonged to US funds – $11.1 trillion (ICI, 2010, Fact Book, page 22).

[2] According to Hedge Fund Research database, at the year-end 2008 hedge funds worldwide managed about $1,407 billion.

domestic equities and debt, and the entire range of derivatives, take undiversified positions, sell short and lever up the portfolio (see, e.g., Fung and Hsieh, 1997, Liang, 2000). In contrast, mutual funds usually do not sell short, do not borrow, and make limited use of derivative securities (Koski and Pontiff, 1999).

In general, hedge funds can be best defined by their freedom from the Investment Company Act's (1940) rules. The Investment Company Act bounds fund leverage, short selling, level of holdings of other investment companies' shares, as well as level of holdings of a single company shares. The hedge fund manager compensation scheme is usually composed of a minimum investment, an annual fee (of about 1% - 2%), and an incentive fee of annual profits (which range may fluctuate between 5% and 25%). The scheme is typically benchmarked against an index or at 0% return each year, and often includes a so called "high water mark" – a stipulation appending past underperformance thresholds to the latest one.

Hedge funds are often structured as limited liability companies or limited partnerships primarily targeting for high net worth individuals and institutions.[3] Investment flexibility and freedom from regulatory control limiting activity of competing investment companies comes at the cost of boundaries on public advertising. Simultaneously, the lack of regulatory control implies difficulties for current and potential hedge fund investors in extracting reliable information on the funds. Moreover, the same regulatory rules prevent the funds opportunity to spread information on their activities even if it were in funds' interest to do so. This may be one reason why relatively little is still known about the hedge fund industry.

Despite the fairly poor information about hedge funds, the industry attracts increasingly growing investors' interest. Evidence on the hedge funds' historical risk and return characteristics suggests that hedge funds may be a valuable portfolio asset (Brown and Goetzmann (2003), Amenc, Faff and Martellini (2002)).

The first hedge fund, which was founded by Alfred Winslow Jones in 1949, was a "market neutral" fund taking long positions in undervalued securities and funding these positions by taking short positions in overvalued securities. This was the "hedge" aiming to leverage the investment in the way allowing to make maximally high bets with limited initial

[3] The National Securities Markets Improvement Act of 1996 limits a number of participants to at most 500. Moreover, according to the National Securities Markets Improvement Act only "qualified investors" defined as individuals who have at least $5 Million to invest and institutions with assets of at least $25 Million are allowed to participate.

investment resources. Following the success of Jones' fund, many new hedge funds, whose managers tried to imitate Jones' "market neutral" strategy, were founded in the latest '60s (Lhabitant, 2007, "Handbook of Hedge Funds"). Nowadays hedge funds are anything but a homogeneous industry which can be treated as a single asset class (Brown and Goetzmann (2003)). The hedge funds can be distinguished by wide range of different investment strategies ranging far from the original Jones' "market neutral" one.[4] Thus, some hedge fund managers create value through unique trading skills, others through implementation of superior asset pricing models, and others through advanced knowledge of particular asset markets. The diversity of strategies applied by different hedge fund managers, however, complicates benchmarking and evaluation of fund managers' performance.

To allow appropriate benchmarking, hedge funds, like many other investment classes, are often classified by investment styles revealing the investment strategy that a hedge fund follows (see, e.g., Brown and Goetzmann (2003), Agarwal, Daniel and Naik (2004)). Thereby, an investment style represents a key element in inferring a fund's risk exposures and serves as a benchmark for performance evaluation of hedge fund managers (see Agarwal, Daniel and Naik, 2000).

According to the results of a survey conducted by Alternative investment Management Association in 2003, about half (47%) of the hedge fund industry participants (consultants, investors, and fund managers) use one or more classifications as defined by outside classification systems, while merely few (3%) argue that there is no way to classify hedge funds (Lhabitant, 2007, "Handbook of Hedge Funds").

There is no commonly accepted rule to categorize hedge fund strategies. In their works, Fung and Hsieh (1997, 1999) claim that the return characteristics are the ones that determine the style of hedge fund strategies. In their study from 1997 they determine four broad styles: *Directional*, *Relative Value*, *Security Selection*, and *Multi-Process Traders*. The same classification is suggested by Brown and Goetzmann (2003). Agarwal and Naik (2000) divide hedge funds into two generalized classes: *Directional* and *Non-Directional*. There are other classifications in the hedge fund literature. For instance, Harri and Brorsen (2004) classify hedge funds into seven styles: *Global*, *Regional*, *Market Neutral*, Short *Sales*, *Long Only*, *Event Driven*, and *Macro Strategies* as fund styles. Okunev and White (2003) distinct

[4] Accordingly, investment strategy determines the investment approaches a fund manager implements and array and type of financial instruments he used to operate with.

for six different styles – *Convertible Arbitrage*, *Fixed Income Arbitrage*, *Credit Trading*, *Distress Securities*, *Merger Arbitrage*, and *Multi-Process – Event Driven*. Many other alternatives exist as well. To identify hedge fund style, we use the TASS style classification, which is similar to the classification suggested by one of the most accepted systems - CS/Tremont.[5]

The importance of the hedge fund investment style is widely documented by existing academic literature. Agarwal, Daniel and Naik (2000) conduct a so-called generalized style analysis[6] to test the risk-return tradeoffs. The authors report that *Directional* strategies demonstrate lower Sharpe ratios and higher downside risk as compared to the *Non-Directional* strategies. Overall, the authors find that the risk exposures are mostly consistent with the investment objectives[7] of the different hedge fund strategies. Amenc, Faff and Martellini (2002) show significant diversification benefits by adding hedge funds, diversified at style level, to an investors' portfolio. Brown and Goetzmann (2003) verify a number of management styles. They find that investment styles explain about 20% of the cross-sectional variability in hedge fund returns. Based on this finding, the authors conclude that appropriate style analysis and style management are crucial in investment decisions of hedge fund investors.

Simultaneously, recent research on investor behavior documents the importance of style information on investment decisions. On the theoretical part, Barberis and Shleifer (2003) introduce the style investing hypothesis. According to this hypothesis investors categorize risky assets into styles and subsequently reallocate their money from previously successful styles into future winners. Furthermore, within style assets are similarly affected from style competition and therefore co-move. There are a number of studies testing relevancy of style investing for different financial sectors. For example, Barberis, Shleifer and Wurgler (2003) assume that index stocks are considered as a separate category, and find

[5] Among most popular classifications appear these of CS/Tremont (27% of users), Hedge Fund Research (27%), MSCI (23%), CISDM, and European and Cogent Hedge database ((Lhabitant, 2007, "Handbook of Hedge Funds").

[6] Classification into generalized styles implies segregation of hedge fund strategies in two groups: directional and non-directional strategies. "The non-directional strategies are designed to exploit short term market inefficiencies while hedging out as much of the market exposure as possible. In contrast, the directional strategies are designed to benefit from broad market movements. These two categories potentially have very different applications: the directional strategies helping one achieve the desired asset allocation while the non-directional strategies enabling one to profit from security selection. " (quotation Agarwal, Daniel and Naik (2000))

[7] Investment objective means the financial goal of investment.

that stocks as soon as they are included in the index co-move more than implied by their fundamentals. Pomorski (2004) tests the impact of style level information on mutual fund flows. The author documents that while at style level money-flows are found to be positively affected by past performance of the style, at individual fund level flows are found to be negatively affected by style performance. These findings contradict the style investing hypothesis, while they are in line with intra-style return chasing.

To the best of our knowledge, none of the existing papers studies the effect of style information on investment decisions of hedge fund investors. At the same time, investigation of the effect that the investment style has on hedge fund investor decision process is especially valuable in light of findings of previous hedge fund literature suggesting that the investment style is one of the determinant characteristics of hedge funds. **Chapter 2** of this thesis examines the way hedge fund investors take into account style information when making their investment decisions.

First, we test for the existence of competition among hedge fund investment styles. In line with Barberis and Shleifer’s (2003) theory, we find that hedge fund styles indeed compete for investors' money. Better performing and more popular styles are rewarded with higher inflows in the subsequent periods.

Next, we examine distribution of money flows within styles. In contrast to Barberis and Shleifer's theory, we find that within style money flows are not equally distributed. Despite that in general style popularity attracts higher investments to the style, within fund competition weakens the style effect. Thereby, better performing and more popular funds within style experience higher inflows in the subsequent periods.

Finally, we test whether the hedge funds' version of style chasing justifies itself. Our results show that the way hedge fund investors chase investment styles appears to be a smart one. In line with the finding of Ding, Getmansky, Liang and Wermers (2007) who show that in the hedge fund flows predict future performance of a fund, we find that style chasing implemented together with search for the best within style funds is profitable. This result implies an ability of hedge fund investors to select funds best-performing in the future.

A number of papers investigate the fund selection ability for mutual fund investors. The investigation of mutual fund investors’ ability to spot the funds that will perform better and move their capital into those funds – known also as the "smart money" effect – was initiated by Gruber (1996). Gruber (1996) attempted to find an explanation for the question why the industry of actively managed mutual funds[8] has grown so fast despite the widespread evidence that on average active fund managers do not add value. According to Gruber (1996), the ability of mutual fund investors to identify better managers, and invest accordingly may justify investing in actively managed mutual funds. Expanding on Gruber's (1996) idea, Zheng (1999) finds that funds with positive net cash flows subsequently demonstrate better risk-adjusted return than funds experiencing negative net cash flows. In addition, Zheng also finds that information on net cash flows into small funds can be used to generate risk-adjusted profits. The more recent research of Sapp and Tiwari (2004), however, claims that the smart money effect reported by previous studies comes from failure of these studies to capture the stock return momentum factor. In contrast to Sapp and Tiwari (2004), Keswani and Stolin (2008) report strong evidence of the smart money effect. The authors claim that Sapp and Tiwari's failure to find a significant relationship between money flows and subsequent fund returns is attributed to their use of – relatively low frequency – quarterly flows.[9]

Nowadays, the number of actively managed funds has continued to grow. Moreover, since the early 1990s, a new class of so-called institutional funds has emerged (James and Karceski (2006)). In contrast to retail funds that focus on regular individuals, institutional funds primarily target institutional investors such as corporations, non-profit organizations, endowments, foundations, municipalities, pension funds, and other large investors, including wealthy individuals. As a result, investor profile of those two types of fund differs as well. More sophisticated institutional investors allocate their money in institutional funds, while retail funds primarily target unsophisticated – individual investors. Given higher level of sophistication of institutional fund investors, they can be expected to demonstrate superior fund selection ability – or a stronger "smart money" effect – than retail fund investors. In **Chapter 3** we reexamine the smart money effect, comparing the fund selection abilities of investors of retail funds, representing mostly unsophisticated individual investors, against this ability of investors of institutional funds, among whom – though a higher proportion

[8] Besides other classifications, mutual funds typically classified into index funds and actively managed funds. Index funds invest in companies whose stocks (or bonds) compose major stock (or bond) indexes, such as the S&P 500. Thus, the performance of index fund are closely approximates this of the index imitated by the fund. In contrast, actively managed funds try to outperform a relevant index through superior stock-picking abilities of their managers and implementation of advanced asset-pricing models and methodologies.

[9] In their study, Keswani and Stolin (2008) use flow data estimated on a monthly frequency.

represents sophisticated investors – are also disadvantaged investors due to account restriction or tax issues.

We explore this question by examining the smart money effect separately for investors of retail and institutional funds.

In line with the studies of Gruber (1996), Zheng (1999), and Keswani and Stolin (2008), we find a smart money effect for investors of both retail and institutional mutual funds. The effect is robust to different measures of performance and flows, and controlling for stock return momentum and investment style. Consistent with the findings of Zheng (1999), we find that the smart money effect comes mainly from small funds. We also observe that investors of both types of funds demonstrate better fund selection ability over expansion periods than during recession periods.

Surprisingly, our results suggest that investors of institutional funds, with a higher representation of more sophisticated investors, do not demonstrate a better fund selection ability.

In addition, the results reported in **Chapter 3** detect a few signs of possible differences in the way investors of the two types of mutual funds make their investment or divestment decisions. The observed dissimilarities in the flows development for retail and institutional mutual funds can be a result of difference in investment decision patterns characterizing investors of each fund type. Since the typical retail fund investor differs noticeably from the typical institutional fund investor in his level of financial sophistication, investment objectives, and search costs (e.g., Alexander, Jones and Nigro (1998), Del Guercio and Tkac (2002), and Palmiter and Taha (2008)), criteria that these two types of investors base their investment decision on are likely to vary, making investment flow patterns of retail and institutional funds differ too.

A bench of mutual fund studies examines investment flows. Edelen (1999) shows that investment flows to a large extent determine fund manager trading activity causing fund managers to engage in liquidity motivated trading that they otherwise would have avoided. In addition, mutual fund research documents that investment flows affect fund manager incentives with respect to risk. Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue that fund manager compensation tied to amount of assets under management together with the convex form of the fund flow-performance relationship, creates incentives for managers to shift fund risk. Johnson (2005) emphasizes the importance of flow examination due to the potential influence of flows on fund performance.

Researchers investigating the determinants of mutual fund flows established the importance of past performance (e. g., Chevalier and Ellison (1997), Gruber (1996), Hendricks, Patel and Zeckhauser (1994), Ippolito (1992), Sirri and Tufano (1998), Ivkovich and Weisbenner (2009), and Ferreira, Keswani, Miguel, and Ramos (2009)). Some of these studies reveal that mutual funds' flow performance relationship has a convex form. For example, Sirri and Tufano (1998) report that individual mutual fund investors allocate asymmetrically more assets in funds with high performance in the previous period. In their recent study Ivkovich and Weisbenner (2009) document that individual mutual fund investors tend to sell recently losing funds, while reluctant to sell the recent winners. At the same time, Del Guercio and Tkac (2002) report that the relationship is convex for retail mutual funds, while it is nearly linear for managers of pension funds. In line with Del Guercio and Tkac's (2002) results, Ferreira, Keswani, Miguel and Ramos (2009), who examine variation in the mutual funds' flow-performance relationship across countries, find that the relationship tends to be less convex in countries with a higher level of economy and a more developed mutual fund industry, explaining their findings by the higher level of financial sophistication of investors, and lower costs of participation in mutual funds attributing developed countries.

Some of the literature shows the effect of flows on fund managers' behavior (e. g., Brown, Harlow, and Starks (1996), and Chevalier and Ellison (1995)). Other studies shed light on the relationship between search costs and fund flows, and the influence of fund marketing and advertisement on flows (e. g., Sirri and Tufano (1998), and Barber, Odean and Zheng (2005), Babalos, Kostakis and Philippas (2009), Ivkovich and Weisbenner (2009)). For instance, Sirri and Tufano (1998) suggest that search costs have an important impact on the investment decisions of individual mutual fund investors. The authors document that high performance seems to be most salient for funds which exert higher marketing efforts as measured by high fees. Media attention, reducing investor search costs, is positively associated with fund flows. Barber, Odean and Zheng (2003) find that mutual fund investors are influenced by salient, attention-grabbing information. They note that investors are more sensitive to salient in-your-face fees, like front-end loads and commissions than operating expenses; they are likely to buy funds that attract their attention through exceptional performance, marketing, or advertising. Moreover, they do not observe any significant relationship between annual flows and fund operational expenses. They explain this result by a positive relationship between fund advertisement efforts and flows, which cancels out the negative effect of the fund expense ratio, embedding advertisement costs. In line with this result, Babalos, Kostakis and Philippas (2009), examining Greek mutual funds, find no relationship between fund expenses and flows. In contrast, Ivkovich and Weisbenner (2009) find that individual investor divestment decisions are sensitive to the fund expense ratio.

However, those studies do not usually distinguish between flows of funds targeting different types of investors. Meanwhile, the growing proportion of institutional funds – both in term of the number of funds and assets under management – makes the recognition and understanding of those differences especially important. In **Chapter 4**, we study determinants of mutual funds' investment flows separately for retail and institutional funds, examining how fund selection criteria vary across investors of these two types of funds. Examination of flows at the monthly frequency allows us to get a more precise picture of fund flows' dynamics as compared to analysis based on quarterly or annually estimated flows.[10]

The results documented in **Chapter 4** indicate a number of differences in the investment flow patterns consistent with client attributes. First, we find that customers of institutional mutual funds react more to such sophisticated performance measures as risk-adjusted returns. On the other hand, flows of retail funds have a stronger relationship with unadjusted performance measures. This result comes in line with the previous research examining investment decision process for individual and institutional investors. Del Guercio and Tkac (2002), for example, find that the typical institutional investor pension fund sponsors, in contrast to individual mutual fund investors, rely more on quantitatively sophisticated fund performance evaluation methods, such as fund Jensen's alpha. Alternatively, summarizing the findings of academic literature that studies mutual fund individual investor's profile, Palmiter and Taha (2008) conclude that the majority of individual investors participating in mutual funds do not take into account the risk and the costs associated with their investments in the funds, and chase past returns.

[10] Barber, Odean and Zheng (2005) investigate mutual fund flows estimated at quarterly frequency; Berk and Tonks (2009), Del Guercio and Tkac (2002), and Sirri and Tufano (1998) study mutual fund flows measured at annual frequency.

We also find that the observed difference in flow-performance relationship increases during recession periods. This finding is consistent with the results of earlier studies of Moskowitz (2000) and Kosowski (2006) suggesting that mutual funds perform better during recessions than during expansions. Moreover, according to those studies, recession periods appear to be the best time to profit from predictability of mutual fund managers' skills. This may explain our results indicating that while investors of both types of mutual funds put higher weight to fund alpha during recessions, more sophisticated investors of institutional funds exhibit even stronger priority for fund risk-adjusted performance over those periods.

Furthermore in this chapter, we compare the form of flow-performance relationship for retail and institutional mutual funds. Consistently with the empirical findings of the previous literature (e. g., Sirri and Tufano (1998), Ivkovich and Weisbenner (2009), Del Guercio and Tkac (2002), Ferreira, Keswani, Miguel and Ramos (2009)), we find that the flow-performance relationship has a non-linear form. However, the form of this relationship is not the same for flows of retail and institutional funds. While for retail funds, the relationship appears to have a convex form, implying that investors of those funds tend to allocate disproportionally more into good performers, but do not punish bad performers by withdrawing money. For institutional funds, however, the form of flow-performance relationship appears to be convex only in the part reflecting disproportional priority of good performers to the rest of the funds. Conversely, the form is concave in the part reflecting punishment of bad performers. This result implies that investors of institutional funds withdraw assets from poor performing funds punishing the worst performers the hardest, while allocating assets into good performing funds, investing more in the best performers.

Our findings on differences in the form of the flow-performance for retail and institutional funds relationship contribute to the extensive literature on incentives and driver factors of fund manager behavior. The convex shape of the flow-performance relationship, observed for the funds of retail fund sample, implies that "winners take all". As a result, fund managers, who are typically compensated as a percentage of assets under management, have an implicit incentive to raise the risk of their portfolios in order to increase their chances to be among the winners, without taking a risk of being punished in case of failure (see, e.g., Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997)). At the same time, the observed concave-convex form of the flow-performance relationship for institutional funds may weaken fund manager incentive to follow the discussed risk-shifting behavior.

Existing mutual fund literature reports that individual fund investors may attempt to reduce search cost using publically available information such as historical performance of a benchmark. For instance, Ivkovich and Weisbenner (2009) show that flows of individual investors into mutual funds are positively related to fund relative performance with respect to its investment objective category (IOC). Similarly, Del Guercio and Tkac (2002) document the importance of a benchmark for both individual and institutional investors. In line with those findings, **Chapter 4** indicates that relative performance of funds, with respect to benchmarks, is an important criterion in the fund selection process. Both institutional and retail funds, outperforming their IOC, experience higher flows than underperforming funds. The benchmark appears to have a stronger influence among investors of retail funds. The influence of the magnitude of the excess returns on fund flows is found to be especially pronounced at the top of the performance distribution.

Moreover, we find a significant negative relationship between investment flows and tracking error – a measure of diversifiable risk – for both institutional and retail mutual funds. Thus, both types of investor punish funds with a higher tracking error through withdrawing assets from those funds, and the tendency appears to be much more pronounced for flows of institutional funds. Furthermore, for institutional funds, the influence of tracking error on investment flows is stronger during expansion periods. In contrary, flows of retail funds are, though weaker than institutional flows, negatively related to the tracking error during bullish periods and positively related to the tracking error during bearish periods.

Furthermore, **Chapter 4** documents evidence suggesting that flows of both types of funds are significantly positively related to fund momentum exposure. The momentum phenomenon implies that well performing stocks tend to continue performing well (Jegadeesh and Titman (1993)). Sapp and Tiwari (2004), investigating the "smart money" effect for a broad sample of domestic equity funds, conjecture that investors tend to allocate their money into ex-post winner funds. As a result, past best-performers disproportionally hold ex-post best-performing stocks. Thereby, reallocating their money into past winners, investors unconsciously benefit from momentum returns on winning stocks. However, analyzing the hypothesis empirically, the authors conclude that higher exposure to the momentum factor does not make a fund more popular, reporting a positive while insignificant relationship between fund momentum exposure and subsequent quarter flows. In contrast, Goetzmann and Massa (2002) document that the investors of index mutual funds exhibit momentum behavior. Contributing to this discussion, Wermers (1997) shows that momentum trading funds succeed consistently to outperform their peers, therefore investment in momentum following funds represent a reasonable strategy.

Consistent with the literature documenting variation of investor behavior across different market conditions, our results show that momentum-trading institutional funds attract considerably higher inflows than their retail counterparts during expansions, while those funds experience relatively lower flows over recessions (see, e.g., Grinblatt and Keloharju (2001), Brunnermeier and Nagel (2004), and Glode Hollified, Kacperczyk, and Kogan (2009)).

We document that both institutional and retail funds with higher inflows in the past continue to experience higher inflows in the subsequent periods (see, e.g., Hendricks, Patel, and Zeckhauser (1993), and Del Guercio and Tkac (2002)). Moreover, this effect appears to be stronger for institutional funds. This result suggests that institutional fund investors exhibit stronger herding behavior, which is in line with the results reported by previous literature (see, e.g., Nofsinger and Sias (1999), Lakonishok, Shleifer and Vishny (1992b))[11]. Finally, studies on the selection of mutual funds posit that individual investors face substantial search costs and are less informed than institutional investors (e. g., Sirri and Tufano (1998), Barber, Odean and Zheng (2003), Ivkovich and Weisbenner (2009)). The results reported in **Chapter 4** reveal that the fund expense ratio also appears to have a significant influence on flows of both types of funds. In particular, mutual funds with lower expense ratio experience higher inflows. Retail fund investors demonstrate stronger sensitivity to the fund expense ratio, and the difference is even larger during recession periods. Probably, investors of institutional funds – being less sensitive to the price of services – due to the fact that they do not invest their own money – are ready to pay for higher quality or more convenient service.

[11] According to Nofsinger and Sias (1999), herding occurs when a group of investors trades in the same direction over a period of time. In addition, the authors denote feedback trading is a special case of herding involving correlation between herding and lag returns.

CHAPTER 2

Style Chasing by Hedge Fund Investors

(This chapter was written in co-authorship with Jenke ter Horst)

This chapter examines whether investors chase hedge fund investment styles. We find that better performing and more popular styles are rewarded with higher inflows in subsequent periods. This indicates that investors compare styles according to style characteristics relative to other styles, and subsequently reallocate their funds from less successful to more successful hedge fund investment styles of the recent past. Furthermore, we find evidence of competition between individual hedge funds of the same style. Funds outperforming their styles and funds with above style average inflows experience higher inflows in subsequent periods. One of the reasons for competition within same style funds is the investors' search for the best managers. The extremely high level of minimum investments limits the diversification opportunities and makes this search particularly important. Finally, we show that hedge funds' version of style chasing in combination with intra-style fund selection represents a smart strategy.

2.1 Introduction

Hedge funds, like many other investment classes, are often classified by investment styles. Long-Short equity hedge, managed futures, event-driven and convertible arbitrage are among the most popular hedge fund investment styles of the past decade. The importance of style classifications grows with the number of individual assets or funds in an investment class. In huge investment classes, like stocks or mutual funds, a portfolio allocation decision based on a selection among styles is often preferred to a selection among individual assets. Today, the number of registered hedge funds far exceeds 10,000. Therefore, we expect that information regarding a hedge fund's investment style has an important impact on the investment decision. This chapter investigates whether hedge fund investors chase well performing hedge fund investment styles and examines the effect of style information on the selection of individual funds within a particular style.

Recent papers investigating investor behavior document evidence on the importance of investment styles (see, for example, Brown and Goetzmann, 2003). According to the style investing hypothesis (Barberis and Shleifer, 2003) investors categorize risky assets into styles and subsequently allocate money to those styles depending on the relative performance of the styles. There are a number of studies testing style investing for different financial sectors (see, for example, Barberis, Shleifer and Wurgler (2003), Pomorski (2004)). However, for our best knowledge, none of the existing papers studies style investing for hedge funds.

Moreover, while some of the current hedge fund literature studies the role of investment style documenting its particular importance, and some investigates factors driving investment decisions, there is none that thoroughly examines the link between investment style and investment decisions. We propose to fill this gap by examining the way hedge fund style is taken into consideration in the investment decision process.

Our study contributes to the hedge fund literature in a number of ways. First, the study includes empirical tests that illustrate whether style investing takes place in the relatively new and dramatically grown asset class of hedge funds. It is interesting and relevant to know whether style investing takes place within this asset class, and, if so, what its impact is on the financial market in general or the hedge fund industry specifically. The inflow of money to the best performing style may have an important price impact on the underlying assets of the investment style. Furthermore, the inflow of money can affect the competition between the funds within the style due to an increase in the number of funds offered with similar style. Eventually, this could lead to a diminishing performance of the style in general. This implies that investors face decreasing returns to scale at style level, in line with Berk and Green's (2004) model at individual fund level. In line with Berk and Green's model, Naik, Ramadorai and Stromqvist (2007) show that capacity constraints at the level of investment styles are responsible for declining risk-adjusted returns over the period 2000-2004.

Second, the chapter examines whether at individual fund level, aggregate style information is taken into account in the investment decision. A substantial part of the hedge fund literature investigates the determinants of individual hedge fund flows. Past performance as well as fund characteristics such as the compensation scheme for the manager, fund manager characteristics, and presence of share restrictions, appear to have a significant impact on fund flows (see, for example, Agarwal, Daniel and Naik, 2004; Baquero and Verbeek, 2006; Ding, Getmansky, Liang and Wermers, 2007; and Li, Zhang and Zhao, 2007). However, none of the previous studies examine whether relative style information has an impact on individual fund flows. Given the huge number of hedge funds available, we expect that style information is an important factor in the choice for a particular hedge fund. In this chapter we will investigate the effect of style characteristics on money flows into and out of hedge funds.

Finally, the chapter examines whether style chasing is a smart strategy for investors. In the case of funds-of-funds, Fung, Hsieh, Naik and Ramadorai (2007) find strong evidence of diminishing returns to scale in combination with inflow of new money in the better performing funds. Naik, Ramadorai and Stromqvist (2007) show that capacity constraints affect future returns of some hedge fund strategies. Hedge fund investors are considered as a more sophisticated investor clientele when compared to mutual fund investors. However, hedge fund investors are confronted with liquidity restrictions due to, for instance, lock up periods. An investment decision in a hedge fund or hedge fund style cannot easily be reversed at a short term. This implies that such an investor needs to be more convinced of the appropriateness and the timing of the investment decision. Although capacity constraints for some strategies may negatively affect future returns at style level, a strategy of style chasing in combination with intra-style fund selection, may nevertheless be a well performing strategy. Therefore it is interesting to examine whether the more sophisticated hedge fund investors are behaving effectively when they increasingly invest in the most popular strategy of the recent past.

Our main findings are as follows. First, we find that the better performing and more popular styles are rewarded with higher inflows in subsequent periods. Style popularity positively affects the subsequent money-flows of funds related to popular styles. Secondly, we find that the style effect is not equal for funds within a style: better performing and more popular funds within a style experience higher inflows in subsequent periods. We explain this result by the presence of intra-style competition, a result that is consistent with Getmansky (2005). A key factor encouraging intra-style competition between funds is the investors' search for the best managers (Li, Zhang and Zhao, 2007; Agarwal, Daniel and Naik, 2008). Apparently, the elevated minimum investment required by individual hedge fund substantially limits diversification opportunities (see, for example, Stulz, 2007), and thereby magnifies the importance of the search for the right manager. Finally, our results show that the way hedge fund investors chase investment styles appears to be a smart one. We find that while style chasing alone does not generate profits, style chasing is profitable when implemented together with the search for the best funds within a particular style.

The remainder of this chapter is organized as follows. In Section 2.2 we describe the data, and we present some summary statistics from our sample of hedge funds. In Section 2.3

we develop and motivate our hypotheses, while in Section 2.4 we formally test the hypotheses and perform a number of robustness checks. Section 2.5 concludes.

2.2 Data

Our survivorship free dataset, provided by TASS, contains information on 2,917 hedge funds reporting in US dollars over the period 1994-2003. For each individual fund, our dataset contains raw returns and total net assets under management (TNA) on the basis reported by the fund (monthly, quarterly, or other). Returns are net of all management and incentive fees. From our initial sample we exclude 156 closed-end funds that are present in our database, since subscriptions to these funds are only possible during the initial issuing period. Furthermore, we exclude 487 fund-of-funds (FOFs), which have a different treatment of incentive fees and may have different performance characteristics. Another important reason for excluding FOFs from the sample is the difference in investor composition between FOF and individual hedge funds. While a majority of FOF clients are private investors, clients of individual hedge funds are mostly so-called high net worth individuals and institutional investors. Hence, clients of FOFs and those of individual hedge funds may differ in their levels of sophistication. Therefore FOFs investors may follow a different decision making process than investors allocating their money to individual hedge funds.

We use quarterly data, which allows us to explore the short-term dynamics of investment and redemption behavior. Quarterly data reduces the patterns of serial correlation that characterize hedge fund returns when these are analyzed on a monthly basis (Getmansky, Lo and Makarov, 2004). We value total net assets (TNAs) per quarter for the most recent quarters available. Furthermore, we restrict attention to funds with a minimum of 5 quarters of return history and with quarterly cash flows available for at least 5 quarters. While the last selection imposes a survival condition, it ensures that a sufficient number of lagged returns are available in order to estimate our models. We exclude observations with extreme changes in TNAs. All observations with changes higher than 300 percent (there were 83 such observations) or lower than -90 percent (there were 44 such observations) are excluded. Our final sample contains 2,274 funds and a total of 33,203 fund-period observations. Our sample contains 229 funds at the end of the first quarter of 1994, accounting for about 27 billion US dollars in net assets, and 1,331 funds at the end of the last quarter of 2003, accounting for

195 billion.[12] Hence, the assets under management have grown more than six times over the sample period.

In Table 2.1 we provide some cross-sectional characteristics of individual funds. The table reveals that the average level of minimum investment in an individual hedge fund is remarkably high: above $750,000. Impressively, the highest level of minimum investment is $25 million! The incentive fee can be as high as 50%, while the maximum management fee in our sample of funds is 8%. The majority of the hedge funds (approximately 73%) make use of leverage, and 55% of the funds register that the fund manager invested personal capital.

[Please insert Table 2.1 about here]

According to the results of a 2003 survey conducted by the Alternative Investment Management Association, about half (47%) of hedge fund industry participants (consultants, investors, and managers) use one or more of the style classifications defined by outside classification systems, while only a very few (3%) argue that there is no way to classify hedge funds.[13] Nonetheless, there is no commonly accepted rule to categorize hedge funds. While the hedge fund industry was originally based on a single long-short strategy, today hedge funds use an abundance of different investment strategies. In our study we use the TASS style classification which is similar to one of the most widely accepted systems - CS/Tremont.[14] For robustness checks we also use the classification suggested by Agarwal, Daniel and Naik (2004). They determine four broad styles and we refer to this classification as the ADN styles. Alternative classifications exist as well (see, for example, Okunev and White (2003), Harri and Brorsen (2004)).

[Please insert Table 2.2 about here]

Table 2.2 presents the two style classifications, while Figure 2.1 displays the trend in assets under management for different TASS styles in the industry. The figure shows that the total net assets under management for most styles increased considerably over the sample

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[12] This represents nearly 24% of the total for the entire industry estimated by Hedge Fund Research of about $ 820 billion of assets under management as of 2003 (See Francois-Serge L'Habitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd., graph on the page 21, provided to the author by the Hedge Fund Research database).

[13] See Francois-Serge L'Habitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd.,.

[14] Among most popular classifications appear these of CS/Tremont (27% of users), Hedge Fund Research (27%), MSCI (23%), CISDM, and the European and Cogent Hedge databases.

period. For instance, the most popular style – *Long/Short Equity* – had about ten times the assets under management at the end of 2003 as it had at the beginning of 1994, and the greatest growth is observed in the *Equity Market Neutral* style which increased its holdings over the sample period by a factor of almost 45. At the same time, the difference in the growth rates of hedge fund styles indicates asymmetry in distribution of funds among different styles.

[Please insert Figure 2.1 about here]

We summarize the development of the TNAs' distribution among the industry styles in Figure 2. As illustrated in the figure, the distribution of TNAs among styles varies over the sample period. For example, *Global Macro*, began with the highest TNA and decreased to one of smallest later in the period. Figure 2.2 also demonstrates the cyclical character of the distribution of TNAs. For instance, the *Managed Futures* style has a decreasing share over the first half of the sample period, while it improves its share over the second half of the period.

[Please insert Figure 2.2 about here]

We determine quarterly net money flows into or out of the investment styles as follows:

$$Flow_{i,t} = \frac{\sum TNA_{j,i,t} - (1+R_{i,t}) \sum TNA_{j,i,t-1}}{\sum TNA_{j,i,t-1}}, \qquad (1)$$

where $Flow_{i,t}$ is the growth rate in total net assets under management of style *i* in quarter *t*; $TNA_{j,i,t}$ is the total net assets under management of fund *j* related to style *i* at the end of quarter *t*; $R_{i,t}$ is the return for style *i* realized during quarter ***t*.** Individual fund quarterly net money flows are calculated in a similar way. We calculate the style return as follows:

$$R_{i,t} = \frac{\sum (R_{j,i,t} \times TNA_{j,i,t})}{\sum TNA_{j,i,t}}, \qquad (2)$$

where $R_{j,i,t}$ is the return of fund *j* related to style *i* and realized during quarter *t*. Table 2.3 reports descriptive statistics of the style return for each of the hedge fund styles over the sample period.

[Please insert Table 2.3 about here]

Additionally, figure 2.3 provides an overview of the style returns over the sample period. From the figure it can be inferred that there are no persistently winning or losing styles in terms of raw returns. For example, in the middle of 1997, the *Emerging Market* style had the highest returns and *Dedicated Short Bias* the worst, while at the end of 2000 the situation reversed: *Dedicated Short Bias* was among the leaders while the *Emerging Market* style was among the losers. Moreover, Figure 3 indicates that a time prosperous for one style might be destructive for other styles. For instance, while at the end of 1999 the *Emerging Markets* style's return jumped to more than 30%, *Long/Short Equity Hedge*'s return dropped by more than 50%.

[Please insert Figure 2.3 about here]

Table 2.4 provides descriptive statistics for investment style flows over the sample period. This table illustrates that the average flows into styles are mostly positive. Moreover, none of them exceeds the level of 10%. Interestingly, while this consistent moderate average level might seem to indicate stability of the style flows, when examined over time, the flows are far more volatile. During our sample period, each style went through both a period of dramatic outflow and a period of extremely high inflows. For example, the *Equity Market Neutral* style had the highest level of outflows (-32.66%), losing almost one third of its assets, while in a later period it increased its size by more than one third (36.12%).

[Please insert Table 2.4 about here]

2.3 Hypotheses and Methodology

Our data has illustrated patterns in the market shares of hedge fund investment style market share. From the hedge fund literature it is well known that at the individual fund level, past performance and fund characteristics appear to have a significant impact on the money flows to particular funds. Given the importance currently attributed to style classification, we expect that information about a hedge fund's style affects the money flow to a particular style. In a second stage, investors decide which fund within a particular style to choose.

Brown and Goetzmann (1997) and Chan, Chen, and Lakonishok (2002) study the role of investment styles in the mutual fund industry. The authors find that style classifications are useful in both performance evaluation and return covariation explanation. Dividing mutual funds into styles, Massa (2003) shows that within family fund-switching affects managerial incentives in such a way that they may no longer intend to maximize performance alone. Cooper, Gulen, and Rau (2004) document that mutual funds related to poorly performing styles tend to change their names. These funds thereby attempt to rid themselves of the poor performance image, and to create a winning image, by using a name that invokes the currently popular styles. The authors also reveal that such name changes do not always correlate with actual change of fund strategy. Nevertheless, the name change indeed affects subsequent investors' decisions as shown by increased inflows to the fund.

A number of hedge fund papers investigate the style-performance relation. Agarwal, Daniel and Naik (2000) conduct a so-called generalized style analysis to examine the risk-return tradeoffs.[15] The authors report that directional strategies demonstrate lower Sharpe ratios and higher downside risk as compared to non-directional strategies. Overall, the authors find that the risk exposures are mostly consistent with the investment objectives of the different hedge fund strategies. Amenc, Faff and Martellini (2003) show evidence on significant diversification benefits achieved by adding hedge funds, diversified at style level, to an investors' portfolio. Brown and Goetzmann (2003) find that investment styles explain about 20% of the cross sectional variability in hedge fund returns. Based on this finding, the authors conclude that appropriate style analysis and style management are important elements in the investment decisions of hedge fund investors.

In this chapter we first want to examine the relevancy of style information in the hedge fund industry. We test for the existence of competition among hedge fund investment styles. We expect that hedge fund investors employ style information when making investment decisions. In the hedge fund industry investment style information seems to be particularly important. Style information is one of the few accessible indicators for a hedge funds' strategy, while the strategy itself is a determining characteristic of the fund's activity. Therefore, it is very likely that sophisticated investors, who are prevalent in the hedge fund industry, search for better performance using style information.

[15] Classification into generalized styles implies segregation of hedge fund strategies in two groups: directional and non-directional strategies. "The non-directional strategies are designed to exploit short term market inefficiencies while hedging out as much of the market exposure as possible. In contrast, the directional strategies are designed to benefit from broad market movements. These two categories potentially have very different applications: the directional strategies helping one achieve the desired asset allocation while the non-directional strategies enabling one to profit from security selection." (Agarwal, Daniel and Naik (2000)).

Style investing suggests that relative rather than absolute style characteristics determine the outcome of the competition for investors' money (Barberis and Shleifer (2003)). It implies that when making investment decisions, investors determine whether the return on a certain style index is higher or lower than that of other investment styles. Alternatively, given the high concentration of sophisticated investors present in the hedge fund industry, it is also possible that investors determine their preference for a specific style on a ranking of risk-adjusted returns, or alpha**.** We use the Fama-French three factor model (Fama and French, 1993) as well as the Fung and Hsieh seven factor model (Fung and Hsieh, 2004) to calculate alphas. We calculate alpha for both style and individual fund levels. Since alpha measurement requires a sufficiently large minimal number of data history, all funds with data history shorter than 3 years were excluded from the sample. To complete our analysis, each individual fund has to have at least 5 alpha observations. Hence we had to exclude from our sample observations all individual funds with less than 15 observations of raw returns. Therefore, for the analysis based on risk-adjusted returns or alphas our sample reduced to 9,898 fund observations for 883 funds.

In order to test for the existence of style competition in the hedge fund industry, we use relative style flows and relative style performance, where performance can be measured as a raw or risk-adjusted style return. Our first hypothesis is formulated as follows:

Hypothesis 1: The relative performance and relative flows of an investment style positively affect the money flows of the style.

To measure relative style performance and relative style flows we use simple rankings. For each quarter we rank styles in such a way that the best performer takes the highest rank, and the worst – the lowest. Similarly, style flows are ranked from the highest net flows to the lowest. The number of positions in the ranking is equal to the number of styles. The regression model testing *Hypothesis 1* is:

$$sFlow_{i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times sRnkFlow_{i,t-n} + \sum_{n=1}^{4} \beta_{2,n} \times sRnkR_{i,t-n} + \beta_3 \times sRisk_{i,t} + \\ + \beta_4 \times sSize_{i,t} + \varepsilon_{i,t} \ , \qquad (3)$$

where $sFlow_{i,t}$ represents flows of style *i* at quarter *t*. $sRnkFlow_{i,t-n}$ is the rank of the flows of style *i* at quarter *t-n*. $sRnkR_{i,t-n}$ is the rank of the performance of style *i* at quarter *t-*

n.[16] $sRisk_{i,t}$ is the risk of style i calculated as the standard deviation of the style's quarterly return measured over the previous four quarters. $sSize_{i,t}$ is a control variable for size of the style and calculated as the natural logarithm of the total net assets under management for style i at quarter t.[17]

In line with *Hypothesis 1*, we expect that higher style flows will be accompanied by higher historical style ranks for both flows and performance. To capture the effect of different lockup periods, we include four lags for ranks of style flow changes, and a similar number of lags of style performance. We also control for style risk and style size, taking into account that the possible negative size-flows relation documented by previous studies (Agarwal, Daniel and Naik, 2004) exists at style level as well. We expect that the relative past performance of an investment style creates initial interest in that style, while subsequent investments attract even greater investments (money follows money). "Money follows money" seems to be especially powerful in the hedge fund industry. Style flows reflect the beliefs of investors in the future potential of a specific style. In the case of the hedge fund industry, investors' beliefs are especially meaningful, since this industry is characterized by a relatively high concentration of sophisticated investors. This is in line with the finding of Ding, Getmansky, Liang and Wermers (2007) who show that in the hedge fund industry, a fund's flows predict its future performance.

At the individual fund level, hedge fund literature suggests a variety of factors determining investment decisions. Past performance as well as fund characteristics such as the manager compensation scheme, fund manager characteristics, and presence of share restrictions- appear to have a significant impact on fund flows (see, for example, Agarwal, Daniel and Naik, 2004; Goetzmann, Ingersoll, and Ross, 2003; Baquero and Verbeek, 2006; Ding, Getmansky, Liang and Wermers, 2007; Li, Zhang and Zhao, 2007). Most studies examining the flow-performance relation report a positive relationship between past performance and money flows into and out of the hedge funds (see, for example, Agarwal, Daniel and Naik (2004), Baquero and Verbeek, (2006)). Using annual time intervals, Agarwal, Daniel and Naik (2004) show that the superior performance of an individual hedge fund in a given year lead to higher money-flows into this fund in the succeeding year.

[16] To exclude multicollinearity problem, we first compute correlations for all of the variables included in the analysis. We confirm that the estimated correlations are low enough to allow performance of the discussed analysis.

[17] We perform a robustness test controlling for time effect. We confirm that our results stay qualitatively the same.

Moreover, this relation is found to be convex. Further, the authors demonstrate that persistence of good past performance can be associated with even higher money-inflows. The authors also find that the future performance of larger individual hedge funds with greater inflows tends to be worse. Fung, Hsieh, Naik and Ramadoria (2007) examine the flow-performance relation in the context of fund of funds (FOFs). They document that alpha producing FOFs have substantially higher and steadier money inflows than their less successful rivals. Based on this finding, they conclude that capital inflows influence funds' ability to generate alpha in the future. Most recently, Ding, Getmansky, Liang and Wermers (2007) show that share restrictions have an important effect on the shape of the flow-performance relation. In the absence of share restrictions, a convex relation is found, while in case of share restrictions, the relation appears to be concave. The authors also demonstrate that while in the hedge fund industry fund flows predict future hedge fund performance, this effect is weaker in funds with share restrictions. However, none of the studies cited above examine the influence of style information on hedge fund money flows. Given the huge number of hedge funds available, we expect that style information is an important factor in an investor's choice of a particular hedge fund.

In this chapter we will investigate the effect of style characteristics on money flows into and out of individual hedge funds. For this purpose, we define funds with flows exceeding average style flows as popular and funds outperforming their style as better performing. Note that performance will be measured as a raw or risk-adjusted return. Our second hypothesis is formulated as follows:

Hypothesis 2: The intra-style relative flows and relative performance of hedge funds positively affect the inflows into the individual funds.

We specify the following regression equation:

$$fFlow_{j,i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times fRnkFlow_{j,i,t-n} + \sum_{n=1}^{4} \beta_{2,n} \times fRnkR_{j,i,t-n} +$$
$$+ \sum_{n=1}^{4} \beta_{3,n} \times fFlow_{j,i,t-n} + \sum_{n=1}^{4} \beta_{4,n} \times fR_{j,i,t-n} + \gamma' X_{j,t} +$$
$$+ \sum_{n=1}^{4} \beta_{5,n} \times sRnkFlow_{i,j,t-n} + \sum_{n=1}^{4} \beta_{6,n} \times sRnkR_{i,j,t-n} + \varepsilon_{i,t}, \qquad (4)$$

where $fFlow_{j,i,t}$ are the flows of fund j related to style i at quarter *t*. $fRnkFlow_{j,i,t-n}$ is a dummy variable for measuring a fund's popularity within its style, that takes a value one if the fund has above average style flows in the corresponding quarter *t-n*. $fRnkR_{j,i,t-n}$ is a dummy variable for measuring a fund's success within its style that takes a value of one if the fund has above average style performance in the corresponding quarter *t-n*. $fFlow_{j,i,t-n}$ are the lagged flows of fund j related to style *i*. $fR_{j,i,t-n}$ is the raw or risk-adjusted return of fund j related to style i at quarter *t-n,* and $X_{j,t}$ is a vector of characteristics of fund j related to style i such as risk of the fund, size of the fund, and other characteristics considered as constant over the sample period.[18] $sRnkFlow_{i,j,t-n}$ is the rank of the flows of style i at quarter *t-n,* while $sRnkR_{i,j,t-n}$ reflects the rank of the performance (measured as raw return or risk-adjusted return) of style i at quarter *t-n.* In keeping with our second hypothesis, we expect coefficients for the more popular and for the better performing funds, within their styles, to be significant and positive. Significant coefficients for both these variables would indicate that there is no direct competition among hedge funds of different styles, but rather competition between them via styles. More specifically, significant coefficients of these variables would imply that two funds related to different styles and having all the same characteristics except that one of them is among the leaders in its style while another is among the losers in its style will have significantly different flows in subsequent periods.

A third and related question of interest is whether the strategy of chasing the best performing and most popular investment style, and subsequently investing in the best performing funds within that particular style is a smart strategy for investors. Berk and Green's (2004) model of active portfolio management predicts diminishing returns to scale. The inflow of money into the best performing funds affects the performance negatively due to a limited number of profitable investment opportunities. Naik, Ramadorai and Stromqvist (2007) show that capacity constraints in some hedge fund strategies explain the decline in the alphas of those strategies. In contrast to mutual fund managers, individual hedge fund managers have the option of closing a fund to new investors. In this way they can circumvent the challenge of having to invest significant additional money funds, potentially affecting the fund performance negatively. However, in line with Naik, Ramadorai and Stromqvist (2007), we expect that the inflow of new money to a particular successful style affects the

[18] We perform a robustness test controlling for time and style effects. We confirm that our results stay qualitatively the same.

competition between funds within that style by leading to an increase in the number of funds offered with that same style. This would lead to a diminishing performance of the style in general as shown by Naik, Ramadorai and Stromqvist (2007). However, this outcome does not necessarily imply that the strategy of investing in the best performing and most popular investment style at a certain moment in combination with intra-style fund selection is not a profitable strategy. Our third hypothesis is formulated as follows:

Hypothesis 3: A style chasing strategy in combination with intra-style fund selection is profitable for investors.

To examine whether style chasing implemented together with the search for the best funds with the particular styles is indeed profitable, we construct the following regression equation:

$$\begin{aligned} fR_{j,i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times fRnkFlow_{j,i,t-n} + \sum_{n=1}^{4} \beta_{2,n} \times fRnkR_{j,i,t-n} + \\ + \sum_{n=1}^{4} \beta_{3,n} \times fFlow_{j,i,t-n} + \sum_{n=1}^{4} \beta_{4,n} \times fR_{j,i,t-n} + \gamma' X_{j,t} + \\ + \sum_{n=1}^{4} \beta_{5,n} \times sRnkFlow_{i,j,t-n} + \sum_{n=1}^{4} \beta_{6,n} \times sRnkR_{i,j,t-n} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where $fR_{j,i,t}$ is the raw return or risk-adjusted return for fund *j* related to style *i* at quarter *t*. $fRnkFlow_{j,i,t-n}$ is a dummy variable for within style popularity of a fund that takes a value of one if the fund has above average style flows in quarter *t-n*. $fRnkR_{j,i,t-n}$ is a dummy variable for within style winning funds that takes value one if the fund has above average style performance in quarter *t-n*. We control for individual fund characteristics such as past flows and past performance, risk and size.[19] $fFlow_{j,i,t-n}$ represents the flows of fund *j* related to style *i* in quarter *t-n*. $fR_{j,i,t-n}$ is the raw return or risk-adjusted return for fund *j* related to style *i* in quarter *t-n*. We also control for relative style characteristics. $X_{j,t}$ is a vector of fund characteristics such as risk and size, while $sRnkFlow_{i,j,t-n}$ is the rank of the flows of style *i* in quarter *t-n* and $sRnkR_{i,j,t-n}$ is the rank of performance of style *i* in quarter

[19] We perform a robustness test controlling for time and style effects. We confirm that our results stay qualitatively the same.

t-n. To evaluate hypothesis 3, we test whether better performing and more popular intra-style funds tend to produce higher performance in subsequent quarters.

2.4 Style Chasing

Our first question is whether relative style performance and relative style popularity affect the money flows to a specific hedge fund investment style. Column (1) of Table 2.5 presents the estimation results of equation (3) when performance is measured by raw style returns, while Columns (2) and (3) show the results when performance is measured by risk-adjusted returns based on the corresponding models. In the case of raw style returns, the results reveal that the coefficients of the first three lags of relative style flows and the coefficient of the first lag of relative style performance are significant and positive. Moreover, these coefficients are economically significant. For instance, an increase in the style flow ranking of merely one point contributes 0.8% to the next period style flows. Furthermore, an increase in the style performance ranking of one point increase next period style flows by more than 0.3%. These results suggest that, in keeping with *Hypothesis 1*, popular and better performing styles are rewarded with higher inflows in subsequent periods. In addition, the results show that the impact of style popularity, as measured by ranking past style flows, persists for a longer term than the effect of past style performance. While style popularity boosts style flows for the next three quarters, the effect of relative style performance holds for just a single quarter, and thus is considerably weaker. It appears that the risk associated with a particular hedge fund investment style has a dampening effect on the money flows to that style. When we measure performance as a risk-adjusted style return, we find similar results for past style popularity. However, the impact of lagged relative style performance is no longer significant. Apparently, even sophisticated hedge fund investors consider raw returns as more relevant than risk-adjusted returns in their allocation decision to particular hedge fund investment styles.

[Please insert Table 2.5 about here]

To compare the explanatory power of relative style flows and relative style performance, we run separate regressions for each of these variables[20]. The explanatory power of the regression with relative style flows is almost 18 percent, while that of the regression with relative style performance is only around 5 percent. This difference shows

[20] The results of these analyses will be provided upon request.

that style popularity has a stronger effect on future style flows than relative style performance. These results of our style level analyses show that the better performing and more popular styles are rewarded with higher inflows in the subsequent periods. These findings support the claim that there is style chasing in the hedge fund industry. Apparently, investors divide hedge funds into styles according to the fund's investment strategy, and increasingly invest in the better performing and popular styles. These results are consistent with the style investing theory of Barberis and Shleifer (2003).

However, the above analysis does not exclude the situation where investors do not classify funds into styles, but rather compare funds according to their individual characteristics. In such a situation, if all the best funds composed the best styles and the worst funds composed the worst styles, and then style "competition" would be just an unintended outcome of fund competition.

If this would be the case, we would observe low correlation between relative performance of fund computed with respect to performance of the rest of funds combining the industry and relative performance of fund estimated with respect to performance of other funds in the style to which a particular fund is related. Correspondingly, the correlation between fund popularity measured with respect to this of all hedge funds and the popularity calculated with respect to popularity of funds related to the same style as that particular fund would be low as well. However, statistics summarized in Table 2.6 reveals that the discussed correlations are rather high, weakening, thereby, the direct fund competition argument. Further, we investigate the style chasing effect at the individual fund level, and show that there is no direct competition among individual funds, but only competition through styles.

[Please insert Table 2.6 about here]

At the individual fund level, hedge fund literature suggests that a variety of factors determine investment decisions. The above analysis shows that style information, measured by performance and popularity, is an important driving factor for the inflow of money at style level. Given the vast universe of hedge funds, we expect that style information is also an important factor in the choice of a particular hedge fund.

Table 2.7 summarizes the results of the estimation of Equation 4 in which we test whether the intra-style relative flows and relative performance of hedge funds positively affect the inflows into the individual funds. Column (1) shows the results when performance is measured by raw returns, while Columns (2) and (3) show the results for risk adjusted returns calculated based on the three-factor Fama-French and the seven-factor Hsieh-Fung models respectively.

[Please insert Table 2.7 about here]

In the table we consider three sets of variables, intra-style, fund specific and general. The results in Specification A demonstrate that the intra-style coefficients for all four lags of both – intra-style popularity and intra-style winner as measured by raw returns– are highly significant and positive. This suggests that, in line with *Hypothesis 2*, more popular and better performing funds within a style attract significantly higher money flows than the less popular and poorly performing ones. Intra-style popularity appears to have stronger impact on future flows than performance: flows toa popular fund are expected to be approximately 7% higher in the subsequent quarter than flows to an unpopular one, while flows to a well-performing fund will be granted with an additional 3.5% compared to a poorly performing one. In addition, the results show that the effect of intra-style popularity and performance diminishes over time. For both variables, coefficients of the first lags are more than three times higher than these of the forth. The estimates for the fund specific variables are in accord with results found in existing hedge fund literature. Lagged fund returns have a positive impact on the inflows to the funds, while larger and riskier funds receive less money than otherwise similar funds. The estimates for the general variables show that style popularity has an additional positive impact on the money flows towards a fund. Although the coefficients of the first three lags of relative style popularity are significant and positive, they have comparatively weak economic impact on fund flows. However, should the fund style's popularity move up one position in rank, the fund could expect a 0.55% additional inflows. On the other hand, none of the coefficients of relative style performance are statistically significant. For risk-adjusted returns we find similar results. As we found in the analysis at the style level, performance measured by risk-adjusted returns has marginal impact on individual fund flows. The significant coefficients for intra-style popularity and performance are in keeping with our assertion as to the absence of direct competition among hedge funds, and thereby confirm the presence of inter-style competition. Furthermore, the results show that the effect of style competition deteriorates at the intra-style level.

So far the results of this section confirm the existence of style competition in the hedge fund industry. Many hedge fund investors believe current style popularity and performance ratings are predictive of future winning styles, and they are switching their investments from past losers to past winners. Furthermore, investor' money is not distributed equally among funds within a given hedge fund style. The investors' quest for the best funds leads to intra-style competition for investors' money, and results in higher inflows to the popular and better performing funds within a style.

Once more we will examine whether the strategy of chasing the best performing and most popular investment style, and subsequently investing in the best performing funds within that particular style, is a smart one for hedge fund investors. Since the minimum investment required by individual hedge funds is extremely high, diversification opportunities for investors are limited (Stulz, 2007). This accentuates the importance of the search for the best manager, or alternatively, for the best qualified managers, within a given style. Thus, the search for the best funds within a given style creates competition for investors' money among funds of the same style.

As noted above, Berk and Green's (2004) model of active portfolio management predicts diminishing returns to scale. According to the model, increased asset flow to successful funds leads to decreased performance by those funds due to the limited number of profitable investment opportunities. Hedge fund managers, however, can prevent the negative effect of money inflows by closing a fund to new investors. At the same time, increased asset flow to a successful style leads to an increase in the number of funds within that style. . In order to analyze the factors affecting the number of funds within a specific style, we have to distinguish between two opposing processes: the introduction of new funds versus the liquidation of existing ones. Here, it is important to note that hedge funds report mostly on a voluntary basis. Moreover, the majority of newly created funds tend not to report at the beginning of their activity, but rather to wait until they can document respectable rates of return. Even so, most hedge funds will continue reporting even up until a liquidation. We expect that style popularity has a positive effect on the survivorship of individual funds within the style, and thus that higher style popularity should be associated with a decrease in the number of liquidated funds within the style.

To test the above suggestions, we performed the following regression analyses:

$$sNo.newF_{i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times sRnkFlow_{i,t-n} + \beta_2 \times sRisk_{i,t} + \beta_3 \times sSize_{i,t} + \varepsilon_{i,t}, \quad (6)$$

$$sNo.deadF_{i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times sRnkFlow_{i,t-n} + \beta_2 \times sRisk_{i,t} + \beta_3 \times sSize_{i,t} + \varepsilon_{i,t}, \quad (7)$$

where $sNo.newF_{i,t}$ in Equation (6) represents the number of funds related to style i and reporting for the first time at quarter *t* so that the regression analysis illustrates the influence of style popularity on the number of new funds within a style. An analogous regression analysis – expressed by Equation (7) – is used to illustrate the influence of style popularity on the number of liquidated funds within a style. Respectively, $sNo.deadF_{i,t}$ in Equation (7) represents the number of funds related to style *i,* and reporting for the last time in the quarter *t* -1, in the regression testing the effect on the number of liquidated funds. $sRnkFlow_{i,t-n}$ is the rank of the flows of style i at quarter *t-n.* $sRisk_{i,t}$ is the risk of style i calculated as the standard deviation of the style's quarterly return measured over the previous four quarters. $sSize_{i,t}$ is a control variable for size of the style and measured as the natural logarithm of the total net assets under management for style *i* at quarter *t.*

In Table 2.8 we present results of the analysis testing the influence of style popularity on the number of new and liquidated funds within a style (Panels A and B of Table 2.8 respectively). In keeping with our predictions, the effect of style competition for investors' money on the number of newly founded funds is not detected. At the same time, the results reveal a negative relation between past style popularity and the number of liquidated funds within the style, implying that higher style popularity predicts a lower number of liquidated funds within the style in the subsequent period. This result is in keeping with previous studies examining factors affecting survival probabilities (see, for example, Baquero, Ter Horst and Verbeek, 2005).

[Please insert Table 2.8 about here]

Table 2.9 reports the results of Equation (5). The results of the regression analysis show that the coefficient of the second, third and fourth lags of the best intra-style performers are significant and positive. These findings indicate that funds outperforming their style tend to perform better in the subsequent periods. The effect of the relative performance of the past half a year appears to be the strongest. Thus, a fund that outperforms its style could be expected to have a return over the next half year that is 1.13% higher than a fund that underperforms its style. It should be noted that the past half year relative performance has the strongest impact on fund flows as well. This result testifies to the effectiveness of hedge fund investors' form of style chasing.

Furthermore, the regression results show that the coefficient of the first lag of intra-style popularity is highly significant and positive. This suggests that intra-style popular funds show significantly better performance in the next quarter. This result contradicts to Berk and Green’s model that predicts diminishing returns to scale. Thus, controlling for fund and style characteristics, it appears that fund’s popularity within its style will lead it to outperform an unpopular fund within the same style by 0.59%. The effect of longer lags of intra-style popularity is less clear. Their coefficients are twice lower than the first lag coefficient, and one of them is negative. However, as previous results show, investors take intra-style fund popularity into consideration mostly over a half year horizon (see Table 2.7). Thus, in keeping with our prediction, in the hedge fund industry, style chasing implemented together with the search for the best funds within a particular style appears to be a successful strategy.

[Please insert Table 2.9 about here]

We explain these results by arguing that while in the hedge fund industry the investing style is one of main determinants of performance, fund specific characteristics such as managerial abilities are crucial as well. Hedge fund style can help to identify groups of funds with potentially successful investment strategies. At the same time, individual characteristics of funds help to identify funds that are able to apply the strategy most effectively. It has to be mentioned that style characteristics serve as a benchmark in the evaluation of individual fund quality.

As is mentioned in Section 3.3 of this chapter, statistics on the hedge fund industry shows that the majority of its participants use style classifications. Nonetheless, there is no commonly accepted categorization of hedge funds strategies. In our study, we use the style classification provided by TASS to perform the main analysis. Since this style classification is not the only one common in the hedge fund sector, we go through all the steps of our analysis a second time, this time applying the style classification suggested by Agarwal, Daniel and Naik (2004). The authors use an extensive database which includes data provided by different vendors, each of whom uses his favorite style classification. To define a common classification for their dataset the authors follow the approach of the studies of Fung and Hsieh (1997) and of Brown and Goetzmann (2003), which demonstrate that hedge fund returns include distinct style factors. The authors thereby reclassify all funds in their database into four categories (see Table 2.2). This broad classification may serve as a useful common denominator for the style classifications used by the main information services providers.

Appendix 2.1 reports the results of the analysis based on the ADN style classification. As illustrated by the appendix, these results are in keeping with those arrived at using the TASS classification, the style related coefficients at both the style and the individual fund levels are slightly higher than the corresponding coefficients of the analyses based on the TASS classification. Most importantly, these results provide strong support for the findings of our main analysis: the considerable effect of style on investment decisions in the hedge fund industry.

2.5 Conclusion

In our study we examine whether hedge fund investors chase investment styles, focusing on the style effect in investment decisions. We find that indeed hedge fund styles compete for investors' money. More specifically, our results indicate that investors tend to actively pursue better performing styles and reallocate their capital from formerly successful styles to future winners. These findings are in accord with the style investing theory of Barberis and Shleifer (2003). We suggest that hedge funds investors are looking for the best investment strategy using style parameters such as the relative flows of the styles and the relative performance of the styles. As a result, better performing and more popular styles are rewarded with higher inflows in the subsequent periods.

Furthermore, we find that investment flows into a given style are not equally distributed among the funds so styled. While a popular style attracts higher overall investments, intra-style competition weakens this style effect. Better performing and more popular funds within a given style experience higher inflows in the subsequent periods. We explain this result by positing existence of intra-style competition, stimulated by investor pursuit of the best funds. Additionally, style analysis, as a key element in inferring the risk exposures of fund managers, helps in classifying fund managers and determining an appropriate benchmark for their performance evaluation (see Agarwal, Daniel and Naik, 2000).

Finally, we test whether the hedge funds' version of style chasing justifies itself. Our results show that the way hedge fund investors chase investment styles appears as a smart one. We find that style chasing implemented together with search for the best funds within the given styles is profitable.

2.6 Tables, Figures, and Appendix (Chapter 2)

Table 2.1
Descriptive Statistics of Cross-sectional Characteristics of Individual Hedge Funds

This table presents summary statistics on some of the cross-sectional characteristics of our sample for the period between the 1st quarter of year 1994 and the 4th quarter of year 2003. *Live Funds* is a dummy variable with value one for funds reported as lived at the end of the sample period. *Minimum Investment* is the monetary value in millions of US $ that an investor is requested to allocate to invest in a fund. *Management Fee* is a percentage of the fund's net assets under management that is paid annually to the managers for administering a fund. *Incentive Fee* is the percentage of profits above a hurdle rate that is given as reward to the managers. *High Water Mark* is a dummy variable with value one for funds having this type of policy. *Leveraged* is a dummy taking the value one if the fund makes active and substantial use of borrowing according to TASS definitions. *Personal Capital* is a dummy variable indicating that the manager invests his or her own wealth in the fund. *Open to Public* is a dummy variable with value one for funds open to public investments. *Domicile Country US* is a dummy variable with value one for funds whom domicile country is US.

Fund Characteristics	Mean	St. Dev	Min.	Max.
Live Funds	0.65	0.48	0	1
Minimum Investment (mill.$)	0.76	0.14	0.001	25.00
Management Fee (%)	1.42	0.87	0	8
Incentive Fee (%)	18.70	5.28	0	50
High Water Mark	0.41	0.49	0	1
Leveraged	0.73	0.44	0	1
Personal Capital	0.55	0.50	0	1
Open to Public	0.13	0.33	0	1
Domicile Country US	0.49	0.50	0	1

Table 2.2
Hedge Fund Style Classifications: TASS versus ADN[21]

This table presents the style classifications used in this chapter. Panel A lists the classification provided by TASS and used in the main analysis. Panel B lists the style classification suggested by Agarwal, Daniel and Naik (ADN) in their paper from 2004. We use ADN classification in the robustness analysis.

Panel A	**Panel B**
TASS Style Classification	ADN Broad Strategy
Convertible Arbitrage	Relative Value
Equity Market Neutral	
Fixed Income Arbitrage	
Dedicated Short Bias	Directional Traders
Emerging Markets	
Global Macro	
Managed Futures	
Long/Short Equity Hedge	Security Selection
Event Driven	Multi-Process
Multi-Strategic	

[21] Style classification according to Agarwal, Daniel and Naik 2004.

Table 2.3
Descriptive Statistics of Style Return

This table presents descriptive statistics of investment flows to the corresponding TASS styles for the period between the 1st quarter of 1994 and the 4th quarter of 2003. The style return (Ri,t) for style i over quarter t is measured as $R_{i,t} = \sum(R_{j,i,t} \times TNA_{j,i,t}) / \sum TNA_{j,i,t}$(In this equation, the term $TNAj,i,t$ represent the total net assets for the fund j - related to style i - at the end of quarter t , and $Rerj,i,t$ represents the return of fund j related to style i and realized during quarter t). The statistics is presented in percents.

	Mean	Median	25th percentile	75th percentile	St. Dev	Max.	Min.
Convertible Arbitrage	2.60	3.10	1.78	4.20	2.49	6.49	-5.94
Dedicated Short Bias	1.41	-0.19	-6.46	8.23	9.46	22.18	-14.21
Emerging Markets	4.47	5.34	-4.74	11.04	11.96	33.56	-24.00
Equity Market Neutral	2.50	2.56	1.58	3.39	1.14	4.52	-0.18
Event Driven	2.80	3.26	2.15	4.45	2.49	6.81	-5.80
Fixed Income Arbitrage	2.15	2.60	1.28	3.37	2.00	5.41	-4.09
Global Macro	3.55	3.15	0.06	8.00	7.03	17.97	-14.10
Long/Short Equity Hedge	1.85	3.50	-1.30	6.95	10.38	16.35	-53.86
Managed Futures	2.94	2.09	-1.47	5.71	5.83	17.73	-5.51
Multi-Strategic	3.09	2.37	-0.83	5.13	7.26	31.07	-7.45

Table 2.4
Style Investment Flows over the Sample Period

This table presents descriptive statistics of investment flows to the corresponding TASS styles for the period between the 1st quarter of 1994 and the 4th quarter of 2003. The investment flows (Flowi,t) for style *i* over quarter *t* is measured as $Flow_{i,t} = (\sum TNA_{j,i,t} - (1 + Ret_{i,t}) \times \sum TNA_{j,i,t-1})/(\sum TNA_{j,i,t-1})$ (In this equation, the terms *TNAj,i,t-1* and *TNAj,i,t* represent the total net assets for the fund *j* - related to style *i* - at the end of quarter *t-1* and *t* respectively, *Reri,t* represents the style's return realized during quarter *t*). The statistics is presented in percents.

	Mean	Median	25th percentile	75th percentile	St. Dev	Max.	Min.
Convertible Arbitrage	7.17	4.79	-0.33	12.08	19.04	110.74	-17.47
Dedicated Short Bias	5.43	6.74	-3.79	10.28	13.98	61.06	-19.57
Emerging Markets	3.05	1.66	-2.54	7.10	10.43	43.15	-17.70
Equity Market Neutral	8.50	6.16	2.24	13.74	11.78	36.12	-32.66
Event Driven	4.03	3.41	1.54	7.20	5.20	17.03	-8.86
Fixed Income Arbitrage	5.20	5.23	1.07	11.31	8.21	20.64	-14.89
Global Macro	-0.93	-2.43	-6.38	4.33	12.64	29.00	-44.57
Long/Short Equity Hedge	4.53	2.85	0.59	4.63	12.75	78.30	-10.39
Managed Futures	3.30	3.17	-1.78	8.61	7.46	21.44	-12.71
Multi-Strategic	0.79	1.91	-2.19	4.35	6.54	14.46	-19.84

Table 2.5
Style flows and style competition

This table reports coefficients of a pooled OLS regression of all styles together. The dependent variable is the style flows. The independent variables are rank of style flows - for each quarter we rank style flows in such a way that the style with highest flows has the highest rank, and the one with the lowest flow has the lowest rank, where the range of ranks is equal to the number of styles, and we include four lags of this variable; rank of style return: in Column (1), at each time point, we rank style return in such a way that the style with the highest raw return takes the highest rank, with the lowest – the lowest; in Column (2)/(3), at for each quarter we rank the alpha of style return, calculated based on the three-factor Fama-French model (Column (2)) or on the seven-factor Fung-Hsieh model (Column (3)), in such a way that the style with the highest alpha has the highest rank, and that with the lowest has the lowest rank, where range of ranks is equal to the number of styles, and we include four lags of this variable; style risk – the standard deviation of a style's return for the four previous quarters; style size – the natural logarithm of the total net assets under management of a style at the end of quarter *t*. The standard errors are clustered by styles. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	(1)			(2)			(3)		
	Raw Returns Based Model			Fama-French Alpha Based Model			Hsieh-Fung 7-Factors Alpha Based Model		
	Estimate		St. Err.	Estimate		St. Err.	Estimate		St. Err.
Intercept	3.55		12.748	-28.90	*	17.105	-31.25	*	16.006
Style Flows Rank (1st lag)	0.81	***	0.254	1.14	***	0.336	1.22	***	0.328
Style Flows Rank (2nd lag)	0.50	**	0.201	0.41	*	0.234	0.42	*	0.225
Style Flows Rank (3rd lag)	0.63	***	0.195	0.39	*	0.208	0.33	*	0.200
Style Flows Rank (4th lag)	0.03		0.219	0.09		0.299	0.10		0.271
Style Performance Rank (1st lag)	0.32	**	0.158	0.26		0.293	-0.13		0.289
Style Performance Rank (2nd lag)	0.26		0.162	-0.01		0.436	0.21		0.512
Style Performance Rank (3rd lag)	-0.08		0.171	-0.19		0.323	-0.97	*	0.506
Style Performance Rank (4th lag)	0.06		0.199	0.06		0.324	0.60		0.422
Style Risk	-0.31	***	0.081	-0.24	***	0.088	-0.19	**	0.090
Style Size	-0.53		0.524	0.93		0.673	1.11	*	0.664
R sq. adjusted	0.18			0.17			0.20		
Number of observations	400			250			250		

Table 2.6
Correlation Matrix

The table contains correlation matrix for the following variables: fund's intra-style popularity dummy (*Popular Within Style*) getting value 1 if at corresponding time point fund flows exceed flows of fund's style; well performing-fund dummy (*Winner Within Style*) getting value 1 if at corresponding time point a fund raw return is higher than this of fund's style; fund flow percentile estimated with respect to flows of the rest of funds in the sample. In particular, the range of the percentiles varies from the lowest 10^{th} to the highest 10^{th} percentile. The return percentile is computed the similar way to this used for flows percentile. The reported statistics is calculated based on the relevant variables of all funds in our final sample.

	Winner Within Style	Popular Within Style	Fund Return Percentile	Fund Flows Percentile
Winner Within Style	1.00			
Popular Within Style	0.05	1.00		
Fund Return Percentile	0.68	0.04	1.00	
Fund Flows Percentile	0.06	0.72	0.08	1.00

Table 2.7
Fund Flows and within Style Competition of Funds

The table reports coefficients of a pooled OLS regression of all funds together. The dependent variable is fund flows. The independent variables are popular intra-style - dummy getting value 1 if at corresponding time point fund flows exceed flows of its style, we include four lags of this dummy; winner intra-style – in Column (1)/(2)/(3) dummy has value 1 if at the corresponding time point, the fund raw return/Fama-French return alpha/Fung-Hsieh return alpha is higher than the raw return/Fama-French return alpha/ Fung-Hsieh return alpha of its style, we include four lags of this dummy; four lags of fund flows; in Column (1)/(2)/(3) four lags of fund raw return/Fama-French return alpha/Fung-Hsieh return alpha; fund size – the natural logarithm of the total net asset value of the fund at the end of quarter *t*; risk of fund - standard deviation of fund return for four previous quarters; live fund - dummy getting value 1 if the fund appear to be live at the last quarter of our dataset; minimum investment is in millions of US$ dollar; management fees are in percents; incentive feesare in percents; high water mark policy - dummy getting value 1 if this policy is used by fund; leveraged fund - dummy with value 1 if fund is leveraged; personal capital - dummy with value 1 if personal capital is a part of fund capital; open to public dummy getting value 1 if fund is open to public investments; domicile country US - dummy getting value 1 if domicile country of fund is US; rank of style flows: at each time point we rank styles in such a way that the style with highest flows has the highest rank, and the one with the lowest flows has the lowest rank, where range of ranks is equal to the number of styles, and we include four lags of this variable; in Column (1)/(2)/(3) rank of style raw return/Fama-French return alpha/Fung-Hsieh return alpha: at each time point we rank styles in such a way that style with the highest raw return/Fama-French return alpha/Fung-Hsieh return alpha takes the highest rank, and that with the lowest takes the lowest rank, where range of ranks is equal to the number of styles, and we include four lags of this variable. The standard errors are clustered by funds. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	(1)			(2)			(3)		
	Raw Returns			Fama-French Alpha			Hsieh-Fung 7-Factors		
	Estimate		St. Err.	Estimate		St. Err.	Estimate		St. Err.
Intercept	13.56	***	1.876	1.02		2.988	0.96		2.879
Popular Within Style (1^{st} lag) (dummy)	6.69	***	0.306	5.27	***	0.515	5.40	***	0.514
Popular Within Style (2^{nd} lag) (dummy)	4.55	***	0.307	4.14	***	0.483	4.21	***	0.481
Popular Within Style (3^{rd} lag) (dummy)	2.31	***	0.305	2.47	***	0.475	2.51	***	0.480
Popular Within Style (4^{th} lag) (dummy)	2.18	***	0.300	1.69	***	0.471	1.80	***	0.474
Winner Within Style (1^{st} lag) (dummy)	3.49	***	0.343	1.42	*	0.756	0.31		0.578
Winner Within Style (2^{nd} lag) (dummy)	3.13	***	0.357	0.03		0.836	0.81		0.718
Winner Within Style (3^{rd} lag) (dummy)	1.60	***	0.324	0.33		0.730	-0.15		0.650
Winner Within Style (4^{th} lag) (dummy)	1.08	***	0.327	-0.80		0.652	-1.29	**	0.564
Fund Flows (1^{st} lag)	0.00	***	0.000	0.01		0.006	0.01		0.006
Fund Flows (2^{nd} lag)	0.00	***	0.000	0.00		0.001	0.00		0.002
Fund Flows (3^{rd} lag)	0.00	**	0.000	0.00	*	0.001	0.01	*	0.001
Fund Flows (4^{th} lag)	0.00		0.000	-0.01		0.004	-0.01		0.004
Fund Performance (1^{st} lag)	0.18	***	0.019	0.45	***	0.110	-0.02	*	0.009
Fund Performance (2^{nd} lag)	0.12	***	0.018	-0.17		0.127	-0.00		0.011
Fund Performance (3^{rd} lag)	0.10	***	0.015	-0.36	***	0.108	-0.01		0.010
Fund Performance (4^{th} lag)	0.09	***	0.014	0.12		0.093	0.02	**	0.011
Fund Size	-1.74	***	0.095	-0.82	***	0.150	-0.78	***	0.145
Fund Risk	-0.26	***	0.021	-0.09	***	0.027	-0.08	***	0.028
Live Funds (dummy)	3.26	***	0.304	3.64	***	0.525	3.73	***	0.524
Minimum Investment	0.00	***	0.084	0.00		0.000	0.00		0.000
Management Fee	-0.63	***	0.160	-0.04		0.221	0.01		0.223
Incentive Fee	-0.01		0.023	-0.01		0.034	-0.01		0.034
High Water Mark (dummy)	2.34	***	0.309	1.61	***	0.521	1.62	***	0.521
Leveraged (dummy)	0.29		0.292	0.73	*	0.422	0.75	*	0.426
Personal Capital (dummy)	0.16		0.284	-0.91	**	0.448	-0.93	**	0.451
Open to Public (dummy)	0.14		0.428	-0.38		0.565	-0.44		0.561
Dom. Country US (dummy)	-1.52	***	0.288	-0.46		0.462	-0.42		0.457
Style Flows Rank (1^{st} lag)	0.55	***	0.048	0.45	***	0.087	0.46	***	0.084
Style Flows Rank (2^{nd} lag)	0.41	***	0.046	0.44	***	0.093	0.44	***	0.092
Style Flows Rank (3^{rd} lag)	0.10	*	0.046	0.10		0.098	0.12		0.099
Style Flows Rank (4^{th} lag)	0.019		0.046	0.14		0.097	0.11		0.094
Style Performance Rank (1^{st} lag)	0.08		0.058	-0.12		0.115	-0.01		0.081
Style Performance Rank (2^{nd} lag)	0.07		0.061	-0.05		0.117	0.01		0.099
Style Performance Rank (3^{rd} lag)	-0.03		0.060	0.38	***	0.114	0.15		0.108
Style Performance Rank (4^{th} lag)	0.02		0.057	-0.25	**	0.108	-0.28	***	0.087
R sq. adjusted	0.11			0.06			0.06		
Number of observations	33,203			9,898			9,898		

Table 2.8
The Effect of Style Popularity on Number of New/Liquidated Funds within Style

Panel A:

The table reports the coefficients of a pooled OLS regression of all styles together; the dependent variable is the number of new funds within style; the independent variables are rank of style flows:for each quarter, we rank style flows in such a way that the style with highest flows has the highest rank, and the one with the lowest flows has the lowest rank, where the range of ranks is equal to the number of styles, and we include four lags of this variable; style risk – the standard deviation of a style's return for the four previous quarters; style size –the natural logarithm of the total net assets under management of a style at the end of quarter *t*. The standard errors are clustered by styles. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Estimate		St. Err.
Intercept	-73.195	***	8.605
Style Flows Rank (1st lag)	-0.004		0.129
Style Flows Rank (2nd lag)	0.175		0.124
Style Flows Rank (3rd lag)	0.116		0.115
Style Flows Rank (4th lag)	0.016		0.123
Style Risk	0.343	***	0.110
Style Size	3.393	***	0.369
R sq. adjusted	0.305		
Number of observations	400		

Panel B:

The table reports the coefficients of a pooled OLS regression of all styles together; the dependent variable is the number of liquidated funds within style; the independent variables are rank of style flows:for each quarter, we rank style flows in such a way that the style with highest flows has the highest rank, and the one with the lowest flows has the lowest rank, where the range of ranks is equal to the number of styles, and we include four lags of this variable; style risk – the standard deviation of a style's return for the four previous quarters; style size –the natural logarithm of the total net assets under management of a style at the end of quarter *t*. The standard errors are clustered by styles. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Estimate		St. Err.
Intercept	-35.856	***	5.467
Style Flows Rank (1st lag)	-0.165	**	0.081
Style Flows Rank (2nd lag)	-0.064		0.086
Style Flows Rank (3rd lag)	-0.056		0.079
Style Flows Rank (4th lag)	0.020		0.081
Style Risk	0.136	***	0.049
Style Size	1.773	***	0.252
R sq. adjusted	0.238		
Number of observations	400		

Table 2.9
Fund Performance and Hedge Fund Version of Style Chasing

The table reports the coefficients of a pooled OLS regression of all funds together; the dependent variable is fund return; the independent variables are popular within style –a dummy getting value 1 if at corresponding time point fund flows exceed flows of its style, we include four lags of this dummy; intra-style winner - dummy getting value 1 if for that quarter a fund over-performs its style, we include four lags of this dummy; four lags of fund flows; four lags of fund return; fund size – the natural logarithm of the total net asset value of a fund at the end of quarter *t*; risk of fund – the standard deviation of the fund return for the four previous quarters; rank of style flows: for that quarter, we rank styles in such a way that the style with the highest flows has the highest rank, and the one with the lowest flows has the lowest rank, where the range of ranks is equal to the number of styles, and we include four lags of this variable; rank of style return: for that quarter,we rank styles in such a way that the best performer has the highest rank,and the worst performer has the lowest, where therange of ranks is equal to the number of styles, and we include four lags of this variable. The standard errors are clustered by funds. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Estimate		St. Err.
Intercept	5.72	***	0.818
Popular Within Style (1st lag) (dummy)	0.59	***	0.149
Popular Within Style (2nd lag) (dummy)	0.03		0.150
Popular Within Style (3rd lag) (dummy)	-0.31	**	0.156
Popular Within Style (4th lag) (dummy)	0.32	**	0.143
Winner Within Style (1st lag) (dummy)	-0.15		0.197
Winner Within Style (2nd lag) (dummy)	1.13	***	0.247
Winner Within Style (3rd lag) (dummy)	0.42	**	0.192
Winner Within Style (4th lag) (dummy)	0.91	***	0.200
Fund Flows (1st lag)	-0.00	**	0.000
Fund Flows (2nd lag)	0.00		0.000
Fund Flows (3rd lag)	-0.00		0.000
Fund Flows (4th lag)	-0.00		0.000
Fund Performance (1st lag)	0.09	***	0.017
Fund Performance (2nd lag)	-0.02		0.021
Fund Performance (3rd lag)	0.01		0.015
Fund Performance (4th lag)	-0.06	***	0.015
Fund Size	-0.21	***	0.044
Fund Risk	-0.01		0.022
Style Flows Rank (1st lag)	0.20	***	0.029
Style Flows Rank (2nd lag)	0.04		0.029
Style Flows Rank (3rd lag)	-0.01		0.032
Style Flows Rank (4th lag)	-0.26	***	0.029
Style Performance Rank (1st lag)	-0.14	***	0.030
Style Performance Rank (2nd lag)	0.13	***	0.034
Style Performance Rank (3rd lag)	0.09	***	0.027
Style Performance Rank (4th lag)	-0.15	***	0.029
R sq. adjusted	0.02		
Number of observations	33,203		

Figure 2.1

Total Net Assets per Style over the period between January 1994 and December 2003

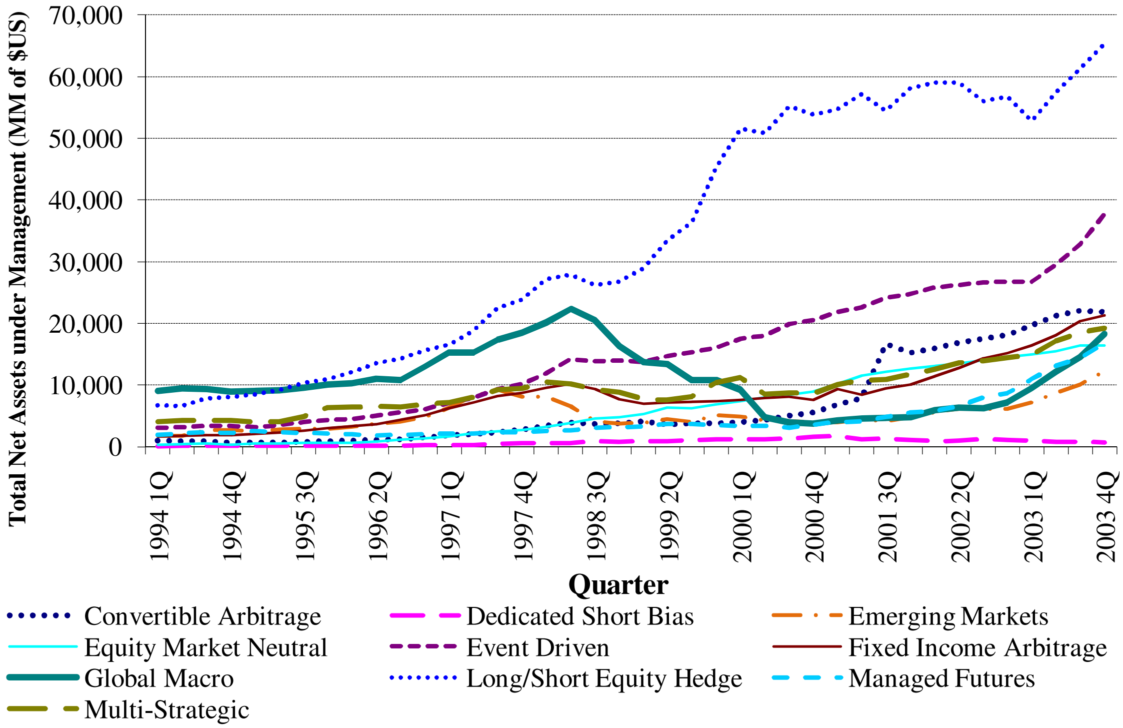


Figure 2.2

Asset Distribution among Hedge Fund Styles over the period between January 1994 and December 2003

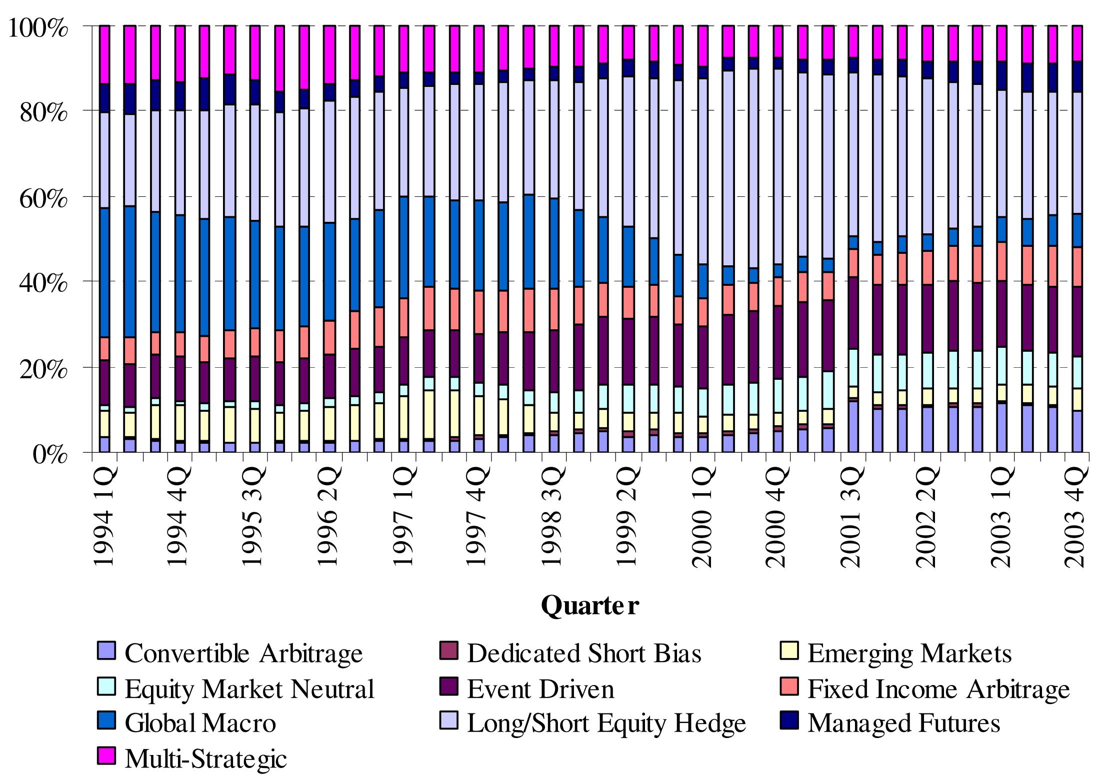
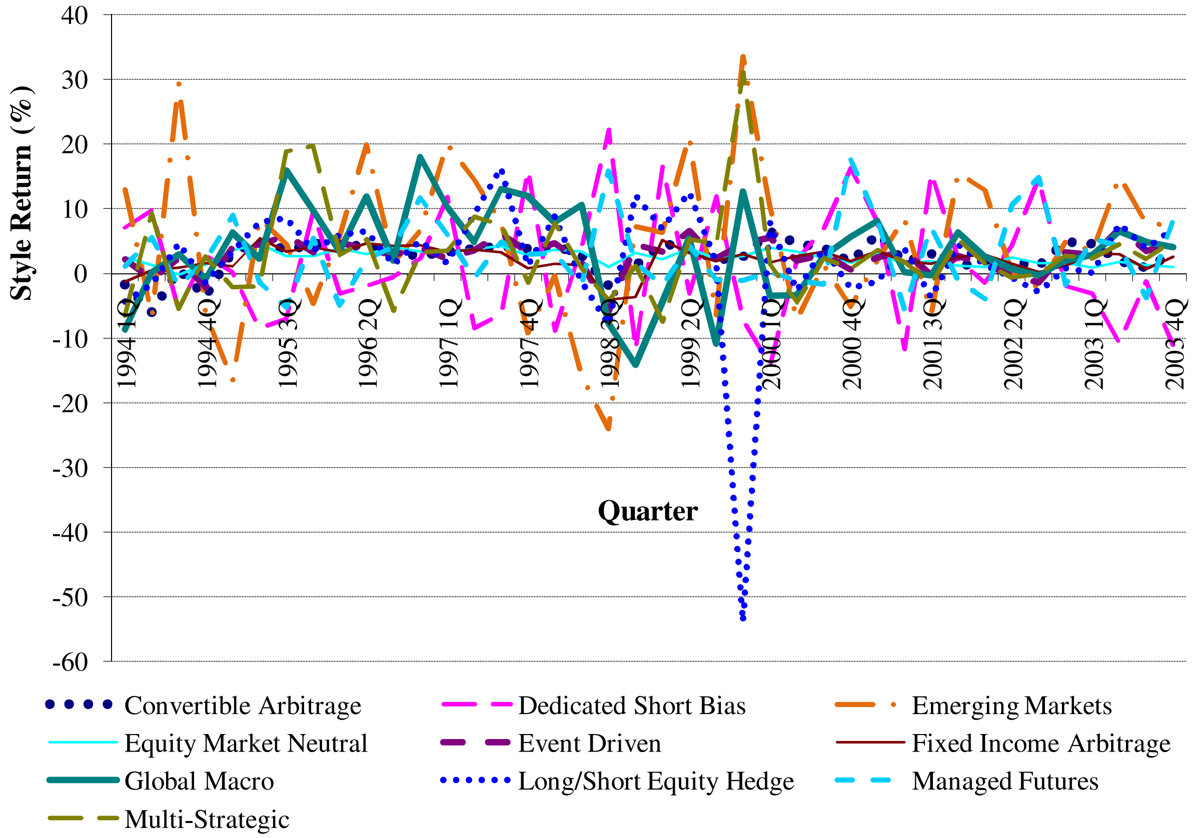


Figure 2.3
Style Returns over the period between January 1994 and December 2003



Appendix 2.1
Robustness - ADN 2004 style classification

Panel A: Style flows and style competition

The table reports the coefficients of a pooled OLS regression of all styles together; the dependent variable is style flows; the independent variables are rank of style flowsfor each quarter, we rank style flows in such a way that the style with highest flows has the highest rank, and the one with the lowest flows has the lowest rank, where the range of ranks is equal to the number of styles, and we include four lags of this variable; rank of style return: for that quarter, we rank style return in such a way that the best performer has the highest rank, and the worst performer has the lowest rank, where the range of ranks is equal to the number of styles, and we include four lags of this variable; style risk – the standard deviation of the style return for the four previous quarters; style size – the natural logarithm of the total net assets under management of a style at the end of quarter *t*. The standard errors are clustered by styles. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Estimate		St. Err.
Intercept	-26.44		20.980
Style Flows Rank (1st lag)	1.29	***	0.475
Style Flows Rank (2nd lag)	1.46	***	0.528
Style Flows Rank (3rd lag)	0.59		0.458
Style Flows Rank (4th lag)	-0.34		0.836
Style Performance Rank (1st lag)	0.20		0.359
Style Performance Rank (2nd lag)	0.65	*	0.370
Style Performance Rank (3rd lag)	0.00		0.360
Style Performance Rank (4th lag)	0.37		0.388
Style Risk	-0.29	***	0.084
Style Size	0.79		0.827
R sq. adjusted	0.18		
Number of observations	200		

Panel B: Fund flows and within style competition of funds

The table reports the coefficients of a pooled OLS regression of all funds together; the dependent variable is fund flows; the independent variables are popular intra-style - dummy getting value 1 if at corresponding time point fund flows exceed flows of its style, we include four lags of this dummy; winner within style - dummy getting value 1 if for that quarter, a fund over-performs its style, we include four lags of this dummy; four lags of fund flows; four lags of fund return; fund size – the natural logarithm of the total net asset value of the fund at the end of quarter *t*; risk of fund – the standard deviation of fund return for four previous quarters; live fund - dummy getting value 1 if the fund appear to be live at the last quarter of our dataset; minimum investment is in millions of US$ dollar; management fees are in percents; incentive fees are in percents; high water mark policy - dummy getting value 1 if this policy is used by fund; leveraged fund - dummy with value 1 if fund is leveraged; personal capital - dummy with value 1 if personal capital is a part of fund capital; open to public dummy getting value 1 if fund is open to public investments; domicile country US - dummy getting value 1 if domicile country of fund is US; rank of style flows: at each time point we rank styles in such a way that the style with highest flows has the highest rank, and the one with the lowest flows has the lowest rank, where range of ranks is equal to the number of styles, and we include four lags of this variable; rank of style return: at each time point we rank styles in such a way that the best performer takes the highest rank, and that with the worst takes the lowest, where range of ranks is equal to the number of styles, and we include four lags of this variable. The standard errors are clustered by funds. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Estimate		St. Err.
Intercept	15.16	***	1.933
Popular Within Style (1^{st} lag) (dummy)	6.95	***	0.333
Popular Within Style (2^{nd} lag) (dummy)	5.20	***	0.324
Popular Within Style (3^{rd} lag) (dummy)	2.43	***	0.329
Popular Within Style (4^{th} lag) (dummy)	2.16	***	0.321
Winner Within Style (1^{st} lag) (dummy)	3.74	***	0.360
Winner Within Style (2^{nd} lag) (dummy)	3.08	***	0.374
Winner Within Style (3^{rd} lag) (dummy)	1.27	***	0.344
Winner Within Style (4^{th} lag) (dummy)	0.88	***	0.343
Live Funds (dummy)	3.40	***	0.303
Minimum Investment	0.00	***	0.084
Management Fee	-0.22	**	0.168
Incentive Fee	-0.02		0.023
High Water Mark (dummy)	2.00	***	0.314
Leveraged (dummy)	0.58	**	0.291
Personal Capital (dummy)	0.11		0.285
Open to Public (dummy)	0.16		0.429
Dom. Country US (dummy)	-1.58	***	0.290
Fund Size	-1.84	***	0.098
Fund Risk	-0.26	***	0.021
Fund Flows (1^{st} lag)	0.00	***	0.000
Fund Flows (2^{nd} lag)	0.00	***	0.000
Fund Flows (3^{rd} lag)	0.00	***	0.000
Fund Flows (4^{th} lag)	0.00		0.000
Fund Performance (1^{st} lag)	0.18	***	0.018
Fund Performance (2^{nd} lag)	0.12	***	0.018
Fund Performance (3^{rd} lag)	0.11	***	0.015
Fund Performance (4^{th} lag)	0.09	***	0.014
Style Flows Rank (1^{st} lag)	0.32	**	0.135
Style Flows Rank (2^{nd} lag)	0.60	***	0.149
Style Flows Rank (3^{rd} lag)	0.62	***	0.127
Style Flows Rank (4^{th} lag)	-0.19		0.135
Style Performance Rank (1^{st} lag)	0.13		0.103
Style Performance Rank (2^{nd} lag)	0.30	***	0.105
Style Performance Rank (3^{rd} lag)	0.28	**	0.111
Style Performance Rank (4^{th} lag)	0.34	***	0.118
R sq. adjusted	0.11		
Number of observations	33,203		

CHAPTER 3

The "Smart Money" Effect: Retail versus Institutional Mutual Funds

Do sophisticated investors exhibit a stronger "smart money" effect than unsophisticated ones? In this chapter, we examine whether fund selection ability of institutional mutual fund investors is better than that of retail mutual fund investors. In line with the studies of Gruber (1996), Zheng (1999), and Keswani and Stolin (2008), we find a smart money effect for investors of both institutional and retail mutual funds. Surprisingly, our results suggest that, the presumably more sophisticated investors of institutional funds, do not demonstrate a better fund selection ability.

3.1 Introduction

More than a decade ago, Martin Gruber (1996) in his paper "*Another Puzzle: The Growth in actively Managed Mutual Funds*" attempted to find a reasonable explanation for the question why the industry of actively managed mutual funds has grown so fast. The main finding of Gruber was that investors in actively managed mutual funds have fund selection ability allowing them to detect future best-performing funds. Gruber defines conditions required for the "smart money" phenomenon to exist. These conditions are superior fund manager abilities and superior ability of sophisticated investors to detect talented managers. Addressing the question why there are still consistently poorly performing funds, Gruber notes that these funds remain due to the presence of "disadvantaged" investors. According to the author, the disadvantaged investor group includes unsophisticated individuals, restricted accounts of institutional investors such as pension funds, and tax disadvantaged investors whose capital gain taxes make divestment of money from a fund inefficient. Gruber's study initiated the whole stream of literature investigating whether mutual fund investors are smart ex ante moving to the funds that will perform better – the "smart money" effect (see, for example, Zheng (1999), Sapp and Tiwari (2004), Keswani and Stolin (2008)).

Nowadays, the number of actively managed funds has continued to grow. Moreover, since the early 1990s, a new class of so-called institutional funds has emerged (James and Karceski (2006)). Instead of focusing on traditional mutual funds' investors – regular individuals, those funds serve exclusively institutional investors such as corporations, non-profit organizations, endowments, foundations, municipalities, pension funds, and other large investors, including wealthy individuals. Thereby, mutual funds were virtually divided into retail and institutional according to their clientele focus. Thus, following Gruber's terminology, clienteles of retail funds, which focus primarily on individual investors, can be classified as an unsophisticated type of disadvantaged investor (Alexander, Jones and Nigro (1998), Del Guercio and Tkac (2002), Palmiter and Taha (2008)), while clienteles of institutional funds either fall into the category of sophisticated investors or into the group of disadvantaged investors of account restriction or tax issue type.

In the context of the "smart money" effect in mutual fund industry, investor composition determines the growth rate of actively managed funds. Following Gruber's line of reasoning, retail and institutional funds, which have different – in terms of Gruber's (1996) investor classification into "sophisticated" and "disadvantaged" types – investor compositions, should grow at a different pace. In fact, the number of institutional funds has increased disproportionally faster (James and Karceski (2006)). Thus, the question to ask is whether Gruber's smart money effect can also explain the difference in the growth rate of retail and institutional funds, and in particular whether investors of these two types of funds indeed demonstrate dissimilar fund selection abilities.

In this chapter we reexamine the smart money effect comparing the fund selection abilities of investors of retail funds, (representing mostly unsophisticated individual investors) against this ability of investors of institutional funds, among whom – though a higher proportion represents sophisticated investors – are also disadvantaged investors, due to account restriction or tax issues.

We explore this question by examining the smart money effect separately for investors of retail and institutional funds. We use the complete universe of diversified U.S. equity mutual funds for the period January 1999 to May 2009 in the CRSP Survivor-Bias Free U.S. Mutual Fund Database. We use CRSP's classification of institutional and retail funds to identify fund types. Note that this classification may not be a precise identifier of investor type. For instance, the final investment decision of 401k plans' participants is taken by an individual investor, while their capital flows may combine flows of either an institutional or a retail fund. Nevertheless, it seems reasonable to assume that the classification of funds into retail and institutional implies differences in investor composition of the two types of fund. In particular, the overwhelming majority of retail fund investors apparently are regular individuals. At the same time, institutional investors, if participating in mutual funds, can be expected to invest in institutional funds. Furthermore, presumably more sophisticated institutional investors influence flows of institutional funds, while flows of retail funds are determined by investment decisions of unsophisticated – individual investors.

Following Gruber (1996), Zheng (1999), Sapp and Tiwari (2004), and Keswani and Stolin (2008), at the beginning of each month and for each type of fund, we construct two portfolios of new-money. The first portfolio consists of all funds with a positive net cash flow realized during the previous month. The second portfolio comprises all funds with a negative net cash flow realized over the same month. Next, we estimate the performance of each of the portfolios in the subsequent month using both the Fama-French's (1993) model and the Carhart's (1997) model including a momentum factor.

To test for fund selection ability on the part of investors of each fund type, we examine the difference between the alphas of the positive and negative cash flow portfolios of the corresponding fund sample. Thus, to compare money smartness of investors of retail and institutional funds, we compare the estimated differences.

In line with the studies of Gruber (1996), Zheng (1999), and Keswani and Stolin (2008), we find a smart money effect for investors of both institutional and retail mutual funds. The effect is robust to different measures of performance and flows, and controlling for stock return momentum and investment style. Consistent with the findings of Zheng (1999), we find that the smart money effect comes mainly from small funds. We also observe that investors of both types of funds demonstrate better fund selection ability over expansion periods than during recession periods.

Surprisingly, our results suggest that investors of institutional funds, with a higher representation of more sophisticated investors, do not demonstrate a better fund selection ability. Probably, performance persistence, widely documented by existing mutual fund literature (Sharp (1966), Grinblatt and Titman (1989a, 1992), Hendricks, Patel and Zeckhauser (1993), Gruber (1996), Elton, Gruber and Blake (1996), Bollen and Busse (2002), Wermers (2003), Kosowski, Timmermann, Wermers and White (2006)), represents one of the main observable attributes of the superior ability of the fund manager, while past return information is accessible and widely used by both types of investors (Alexander, Jones and Nigro (1998), Del Guercio and Tkac (2002), Palmiter and Taha (2008)). If so, a higher level of financial sophistication does not necessarily lead to better fund selection ability. Alternatively, performance persistence, providing some extent of return predictability, together with accessibility of past return records and financial advisers' services, allows unsophisticated investors to demonstrate fund selection ability as well.

Concurrently, our results indicate dissimilarities in the cash flow development for retail and institutional funds. The observed dissimilarities can be a result of difference in investment decision patterns characterizing investors of each fund type (Nofsinger and Sias (1999), Grinblatt and Keloharju (2001), Del Guercio and Tkac (2002), Froot and Teo (2004), Sias (2004), Gallo, Phengpis and Swanson (2008)), and deserve further investigation.

The remainder of this chapter is organized as follows. Section 3.2 provides an overview of relevant literature. Section 3.3 discusses the mutual fund data sample and the methods used to measure cash flows and the performance of new money portfolios. Section 3.4 provides evidence on the performance of the new-money portfolios for both types of funds and discusses the differences in the observed effect for retail and institutional funds. Section 3.5 studies determinants of cash flows into both types of funds. Section 3.6 concludes.

3.2 Overview of related literature

3.2.1 The "Smart Money" hypothesis

The smart money hypothesis postulates that investors are "smart" enough to move to funds that will outperform in the future, that is, that investors have fund selection ability. As noted above, the investigation of the smart money effect in the context of mutual funds was initiated by Gruber (1996). He aimed at understanding the continued growth of the actively managed mutual fund industry despite the widespread evidence that on average active fund managers do not add value. To test whether investors in fact have selection ability, he examines whether investors' money tends to flow to the funds that subsequently outperform. Working with a subset of U.S. equity funds, he finds evidence that money appears to be smart. One potential explanation for this smart money effect is that investors have an ability to identify better managers, and invest accordingly. According to Gruber (1996), this argument provides a justification for investing in actively managed mutual funds.

Zheng (1999) develops the analyses of Gruber (1996), using the universe of all U.S. domestic equity funds that existed between 1970 and 1993. She reports that funds with positive net cash flows subsequently demonstrate better risk-adjusted return than funds experiencing negative net cash flows. In addition, Zheng finds that information on net cash flows into small funds can be used to generate risk-adjusted profits.

The more recent research of Sapp and Tiwari (2004), however, claims that the smart money effect reported by previous studies comes from failure of these studies to capture the stock return momentum factor. Their line of reasoning can be illustrated as follows. Well performing stocks tend to continue performing well (Jegadeesh and Titman (1993)). Simultaneously, investors tend to allocate their money into ex-post best-performing funds. Furthermore, past best-performers inevitably disproportionally hold ex-post best-performing stocks. Thus, relocating their money into past winners, investors inadvertently benefit from momentum returns on winning stocks. To test this argument, Sapp and Tiwari estimate abnormal return on portfolios formed based on net cash flow with and without the stock return momentum factor. They find that accounting for the momentum factor eliminates outperformance of positive cash flow funds. At the same time, the authors show that investors do not rationally pursue to benefit from stock return momentum, and higher exposure to the momentum factor does not make a fund become more popular. Contributing to this discussion, Wermers (2003) investigates holdings of fund portfolios and shows that fund managers who have recently done well tend to invest a considerable portion of new money into the recently winning stocks in an attempt to continue to perform well.

Keswani and Stolin (2008) revisit the smart money debate using a British data set. The authors report strong evidence of the smart money effect for both individuals and institutions in the U.K. They note that while the performance difference between positive and negative net cash flow funds is lower in its magnitude, it is highly significant statistically. The authors also briefly reexamine the effect for U.S. data, and find that when using monthly flows, there is a smart money effect in the U.S. as well, even after controlling for the momentum factor. The U.S. smart money effect is comparable in magnitude to the one they find in the U.K. The authors claim that Sapp and Tiwari's failure to find a significant relationship between money flows and subsequent fund returns in the U.S. is attributed to their use of quarterly flows.[22]

Our study contributes to this stream of literature testing the existence of the "smart money" effect separately for investors of retail and institutional mutual funds. This gives us the opportunity to compare the fund selection abilities for investors of two types of funds, whose investors are presumably different in their level of financial sophistication. In contrast to Keswani and Stolin (2004), who treat flows of individual and institutional investors separately, we estimate the

[22] In their study, Keswani and Stolin (2008) use flow data estimated on a monthly frequency.

differences in the fund selection abilities for the investors of retail and institutional funds statistically.

We use monthly data for all U.S. domestic equity mutual funds that existed over the last decade. Thus, our study tests the “smart money” effect for the most recent period, which was not covered by the previous smart money literature. Monthly flow data allows us to conduct more accurate analysis compared to the one performed by Gruber (1996), Zheng (1999), and Sapp and Tiwari (2004), who use quarterly flow data. While Keswani and Stolin (2008) also conduct the analysis of smart money effect on a monthly level, they concentrate primarily on British data.

3.2.2 Institutional versus Individual Mutual Fund Investors

Studies of mutual funds typically distinguish between individual and institutional investors. For example, studies of fund selection often assume that, individual or so-called “retail” investors, face substantial search costs and are less informed than institutional investors. Other studies argue that institutional investors base their investment decisions on more sophisticated selection criteria than individual investors do (Del Guercio and Tkac (2002), James and Karceski (2006), Birnbaum, Kallberg, Koutsoftas and Schwartz (2008)). Nevertheless, Lakonishok, Shleifer and Vishny (1992) conjecture that investment decisions by some institutional investors are affected by several layers of agency conflicts. Particularly, the authors argue that sponsors of pension funds, trustees and corporate treasurers may entrust outside managers with money management in an attempt to avoid responsibility in the case of poor performance. This can result in the manager selection process being mainly based on past performance, similar to the way retail investors tend to select mutual funds.[23]

Birnbaum, Kallberg, Koutsoftas and Schwartz (2008) discuss how the institutions and retail investors react to past performance, and whether their reactions differ considerably during the bearish or bullish market conditions. The authors document that the reaction of institutions to past performance differs from the reaction of retail investors. In particular, the authors find that institutions react less aggressively to both good and bad performance. Birnbaum et al. (2008) emphasize weak negative reaction to underperformance of both – retail and institutional investors.

[23] According to Lakonishok et al. (1992), the corporate insider responsible for money allocation can easily switch between money managers, relocating the money from a poorly performing manager to a manager who has done well in the past. This way the money manager selection process is based mainly on past performance.

The authors conclude that investors' reluctance to withdraw their money during bearish periods allows mutual funds to experience relatively low outflows, even during adverse market conditions.

Summarizing the academic literature that examines the profiles of mutual fund investors, Palmiter and Taha (2008) report that individual mutual fund investors are mostly financially unsophisticated: they do not take into consideration costs associated with the investment, and tend to chase past returns. Simultaneously, the authors point out that clienteles using the assistance of financial advisers, don't do any better. This conclusion contradicts the findings of Jones, Lesseig and Smythe (2005), who show that financial advisers pay great attention to characteristics such as relative fund performance, fund investment style, fund risk, and manager reputation and tenure, i.e., those characteristics that individual investors do not usually take into consideration or are unable to access.

In their study from 2002, Del Guercio and Tkac argue that due to differences in agency relationships and level of financial sophistication: pension fund sponsors – considered more sophisticated – use different selection criteria in picking their portfolio managers than mutual fund investors, the majority of which are relatively unsophisticated individual investors. In fact, the authors document that the criteria to select portfolio managers are significantly different for pension funds and retail mutual funds. Pension funds are found to use such quantitatively sophisticated measures as tracking error and risk-adjusted returns, such as Jensen's alpha. In contrast, retail mutual fund investors pay greater attention to raw returns. The authors also document significant differences in the flow-performance relationship attributing both types of investors. Thus, the authors confirm that, the presumably more sophisticated pension fund investors also employ more sophisticated measures in selecting a portfolio manager than unsophisticated retail investors do.

At the same time, mutual funds' literature documents evidence on persistence in fund returns, (see, for example, Sharp (1966), Grinblatt and Titman (1989a, 1992), Brown, Goetzmann, Ibbotson and Ross (1992), Hendricks, Patel and Zeckhauser (1994), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Elton, Gruber and Blake (1996), Carchart (1997), Bollen and Busse (2002), Wermers (2003), Kosowski, Timmermann, Wermers and White (2006)). Sharp (1966) finds persistence for both low and high-ranked mutual funds. Hendricks, Patel and Zeckhauser (1993) introduce the concept of "hot hands" meaning the tendency of the best performing funds to continue to outperform in the subsequent periods. Elton, Gruber and Blake (1996) show that past return can serve as a good predictor of future return for the long run as well as the short run. Carhart's (1997) reports persistence in fund performance only over short term horizons of up to one year. Carhart argues that, momentum effect is mostly responsible for the disappearance of performance persistence on the longer horizon, noting that only the worst-performing funds stay bad in the long run. Wermers (2004), documents strong persistence of mutual fund returns over multi-year periods. To summarize: empirical findings investigating performance persistence, do not reject a possibility that, past raw returns and returns estimated on risk-adjusted basis, can predict future return. Thus, "unsophisticated" investors, in their naïve chase for past returns, do not necessarily follow the wrong fund selection strategy.

Therefore, while the existing academic literature provides empirical evidence on differences in fund selection criteria, implemented by sophisticated versus unsophisticated investors, (see for example Del Guercio and Tkac (2002), Birnbaum, Kallberg, Koutsoftas and Schwartz (2008)), it is not clear whether a higher level of financial sophistication essentially implies better fund selection ability.

Alternatively, there is no consensus in the mutual fund literature regarding exceptional abilities of fund managers to generate high returns. Jensen (1967) contends that there is very little evidence of fund managers with genuine timing and picking abilities. In their recent study, Duan, Hu and McLean (2008) find that mutual fund managers exhibit stock-picking ability only in stocks with high idiosyncratic risk. Moreover, the authors document that, in general stock picking ability of mutual fund managers has diminished considerably over the last decade, being negatively affected by the expansion of mutual fund industry itself and intensive growth of competing hedge fund industry. Cuthbertson, Nitzsche and O'Sullivan (2008) show that only a few of the top best-performing U.K. mutual funds demonstrate stock picking ability which is not just due to good luck. Simultaneously, the worst-performers are not found to be unlucky, but rather 'badly skilled'. For U.S. data, Kosowski, Timmermann, Wermers and White (2006) reveal that merely a minority of mutual fund managers have stock-picking ability. Furthermore, Swinkels and Rzezniczak (2009) state that fund managers possess insignificantly positive selectivity skills and they do not appear to possess equity and bond timing skills. Studying hybrid mutual funds, Comer, Larrymore and Rodriguez (2009) suggest that these funds consistently underperform their style benchmarks. This means that managers of those funds exhibit neither timing nor selectivity ability.

To summarize, the question that remains is whether advanced financial sophistication is indeed closely associated with superior fund selection ability. In this chapter, we investigate this question empirically, comparing fund selection ability of individual versus institutional mutual fund investors, when the latter are commonly considered to be more sophisticated.

So far, we have discussed differences between individual and institutional investors. Now, let's take a look at characteristics of funds serving these two types of investors.

3.2.3 Institutional versus Retail Mutual Funds

In US mutual fund industry, funds purely focused on institutional investors represent a relatively recent trend which started in the early 1990s (James and Karceski (2006)). The formation of institutional funds has resulted in a division of mutual funds into individual and institutional oriented. Thus, funds serving individual clienteles are recognized as being "retail" funds, while funds targeting institutional investors are seen as "institutional" funds. There is no formal definition of the retail or the institutional fund. The main criteria usually considered to classify funds into retail and institutional, are minimum investment requirements declared by the fund and the distribution channel of fund shares. Morningstar, for example, classifies as being an institutional fund with minimum initial investment requirements of at least $100,000 (James and Karceski (2006)). In this study, we use fund classification provided by CRSP, which adopts Lipper fund type categorization. Lipper classifies institutional funds as having a minimum investment requirement of at least $100,000 and fund's shares having to be distributed to or through an institution.[24] In addition, funds that designate themselves as being institutional are usually recognized as such.[25]

Although the same companies that have a part in running retail mutual funds (banks, insurance companies, brokers, and fund advisory companies) operate institutional mutual funds, these funds have several distinguishing characteristics. Besides considerably higher minimum initial investments, institutional funds usually offer lower costs to investors compared to retail funds. So, only an insignificant minority of institutional funds have front or deferred loads, redemption fees or 12b-1 marketing expenses.

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[24] We received this information during a phone conversation with one of the Lipper officers responsible for this field.

[25] Both Morningstar and Lipper consider a fund to be institutional if it is designated as such (for Morningstar this information is based on the study of James and Karceski (2006), and for Lipper, based on our e-mail dialogue with one of the Lipper officers responsible for this field)).

The size of the institutional segment of the mutual fund market has grown dramatically in recent years, both in terms of the number of funds and assets under management. For example, James and Karceski (2006) report that at the beginning of their sample period – year 1986 – the number of open-end bond and equity institutional funds was 22, while at the end of the sample period – the end of year 1998 – there were 873 funds. Thus, the number of institutional funds increased 40-fold during the sample period. In contrast, the number of retail funds increased from 786 to 5,076 (an increase of around 650%) during the same period. At the same time, the amount of assets managed by institutional funds grew from 3.2 billion at the beginning of the sample period – year 1986 – to over $302 billion by the end of the sample period – year 1998.

Numbers reported by the Investment Company Institute (ICI) confirm the observed tendency. ICI estimates that institutions held more than 1.7 trillion dollars in equity, bond, money market and hybrid open-end mutual funds at year-end 2008 (out of a total of $9.6 trillion in these funds). That is compared with 0.7 trillion dollar held by institutional investors in mutual funds at year-end 2000, which represented merely 10% of the total assets of the mutual fund industry in the year 2000 (7.3 trillion dollar).[26]

Our sample also depicts considerable growth of proportion of institutional funds. Thus, at the beginning of our sample period – January 1999 - institutional funds represented around 20% of all funds managing merely 12% of assets, while at the end of the period – May 2009 – almost 40% of all funds in our sample were institutional funds accounting for 22% of assets under management.

Figures 3.1 and 3.2 show the evolution of both groups of funds in our sample over the period between January 1999 and May 2009. The number of institutional funds grew at a faster pace than the number of retail funds, with the number of institutional funds increasing 322 percent (from 884 to 2844 funds), and the number of retail funds increasing 53 percent (from 3042 to 4656 funds). Assets under management held by institutional funds increased almost three-fold (from 247 billion to 671 billion), while assets under management of retail funds remained nearly the same (1883 billion to 1840 billion).

[Please insert Figures 3.1 and 3.2 about here]

Some of the institutional funds in our sample have retail counterparts. Since the Investment Company Act requires different classes of shares of the same fund to have the same return before

[26] See, ICI “Fact Book 2009”.

distribution expenses, the institutional and retail shares of such funds, while holding the same portfolio, are claims on separate asset pools or trusts. This structure is imposed by the differences in services that each type of fund requires from the fund manager. For instance, management fees may be lower for the institutional investor shares than for the retail, since institutional sponsors may provide bookkeeping services and transact with the fund through an omnibus account. The institutional and the retail peers file separate prospectuses.

Comparing performance of retail and institutional funds, James and Karceski (2006) find that, despite significantly lower management expenses, the average return on institutional funds is no better than the average return on retail funds. Even on a risk-adjusted basis, institutional funds performance is similar to retail funds. In addition, the authors report that institutional funds with low initial investment requirements and funds with retail peers perform worse than other institutional funds both before and after adjusting for risk and expenses.

Baker, Haslem and Smith (2009) investigate the relationship between the performance and characteristics of domestic, actively managed institutional equity mutual funds. Their results show that large funds tend to perform better, which suggests the presence of significant economies of scale. The authors also document evidence on the positive relationship between cash holdings and performance.

3.3 Data and Methodology

3.3.1 Sample Description

We collect data from the CRSP Survivor-Bias Free US Mutual Fund Database. Our sample comprises all open-end domestic equity mutual funds that existed at any time during the period January 1999 to May 2009 and for which values of monthly total net asset are reported by CRSP. Further, we exclude specialized funds, sector funds, balanced funds and international funds, since risk factors of these funds may differ from risk factors driving the performance of other equity mutual funds. We treat fund-entity as is denoted by CRSP. More specifically, each fund represents either a share class (thereby representing only a part of the fund assets) or a fund representing an entire portfolio. Thus, the final sample contains 11,710 fund-entities comprising 818,530 fund-months.

The CRSP mutual fund sample is fairly close to the opportunity set of equity mutual funds faced by institutional and retail investors in practice. Thus, the results based on this sample should provide a realistic evaluation of fund selection ability for both types of the investors.

We categorize funds as institutional if CRSP designates them as such. Starting in 1999, the CRSP database includes a variable that identifies whether a fund represents institutional or retail type. We use this year as a starting point in our investigation. As mentioned in the previous section, explicit division of funds into institutional and retail, represents relatively recent trends that started in the early 1990s.

CRSP derives the institutional/retail identifier from Lipper, and assigns funds as institutional if they fall into Lipper's "Institutional" or "Bank Institutional" categories. More specifically, Bank Institutional funds are considered to be funds that are primarily offered to clients, agencies and fiduciaries of bank trust departments, commercial banks, thrifts, trust companies, or similar institutions. The bank, bank affiliate or subsidiary acting as advisor, or, in some cases, sub-advisor for the funds, and the funds are typically marketed as a bank product. Institutional funds are considered if they are primarily targeted at organizations and institutions, including pension funds, 401k plans, profit sharing plans, endowments, or accounts held by institutions in a fiduciary, agency or custodial capacity.

Note that this classification may not be a precise identifier of investor type. For instance, the final investment decision of 401k plans' participants is taken by an individual investor, while their capital flows may combine flows of either an institutional or a retail fund. Nevertheless, it seems reasonable to assume that the classification of funds into retail and institutional implies differences in investor composition of the two types of fund. In particular, the overwhelming majority of retail fund investors apparently are regular individuals. At the same time, institutional investors, if participating in mutual funds, can be expected to invest in institutional funds. Furthermore, presumably more sophisticated institutional investors influence flows of institutional funds, while flows of retail funds are determined by investment decisions of unsophisticated – individual investors.

Table 3.1 contains descriptive statistics for the mutual funds of both samples. Therefore, Panels B and C provide corresponding statistics for the retail fund and the institutional fund samples respectively. For purposes of comparison, we also report corresponding statistics for the sample of all funds (Panel A).

As reported in Table 3.1, on average, retail funds are slightly bigger than institutional funds. Thus, the average retail fund in our sample had $505 million under management compared with $247 million managed by the average institutional fund. Presumably, the observed difference in average size is the result of the size difference between the largest retail and institutional funds. More specifically, the largest institutional fund in our sample is roughly two times smaller than the largest retail fund, managing $48 billion and $97 billion respectively. At the same time, the median fund size is almost the same: $29 million for retail funds compared to $27 million for institutional funds.

In addition, Table 3.1 shows that the average expense ratio is considerably lower for institutional funds than for the retail funds. In particular, the average expense ratio for institutional funds (1.02% per year) is 60 basis points lower than the average expense ratio for the retail fund (1.62% per year). Although an expense ratio and maximum front-end load fee are considerably higher for retail funds, we also observe that the turnover ratio is similar for both samples.[27]

The average monthly new cash flow, described in this section below, into funds is positive for retail funds as well as for institutional funds. However, the average monthly net cash flow for institutional funds is nearly four times higher than for retail funds ($1.73 million and $0.44 million correspondingly). If we normalize the net cash flow by fund TNA of the prior month, the average normalized monthly cash flow is much more similar for both types of funds.[28]

[Please insert Table 3.1 about here]

The institutional funds in our sample seem to perform slightly better. Lower brokerage commissions and expenses, characterizing institutional funds, are possible sources of return difference. Moreover, some of the institutional funds in our sample have retail counterparts. Such retail "peers" are equity funds with the same advisor and fund name as the institutional funds, but with different share classes. In these cases, institutional and retail "peers" hold exactly the same equity portfolio and have identical fractional cash balances. Thus, the only source of differences in their returns can be the differences in paid brokerage commissions and expenses.

[27] Expense ratio for retail funds is 1.62%, and 1.02% for institutional funds. Maximum front-end load fee is 3.40% for retail funds, and 1.50% for institutional funds.
[28] Average Monthly Normalized Cash Flow for retail fund is 1.82%, and 2.13% for institutional fund.

Before commencing our work with our flow data at the fund-month level, we eliminate fund-months without records for fund total net asset value. This leaves us with 817,423 fund-months, from which 576,975 are retail fund-months and 240,448 institutional fund-months. In addition, we exclude fund-observations with 1st and 99th flow percentile, so that highly unusual flows do not drive our results. More specifically, exceptionally noisy flow data can be an attribute to very young funds or funds about to be closed down.

3.3.2 Measurement of Cash Flows and Performance

Following the existing "smart money" literature (see for example Zheng (1999), Sapp and Tiwari (2004)), we examine investors' fund selection ability by estimating the performance of new-money portfolios, which are constructed based on a signal of the fund's realized net cash flow. At the beginning of each month and for each type of fund, we construct two portfolios of new-money. The first portfolio consists of all funds with a positive net cash flow, realized during the previous month. The second portfolio comprises all funds with a negative net cash flow, realized over the same month. Since both portfolio types are formed based on the signals of a new cash flow, we refer to those portfolios as new money portfolios. We measure the net cash flow to fund *j* during month t as follows:

$$NCF_{j,t} = TNA_{j,t} - TNA_{j,t-1}\left(1 + R_{j,t}\right). \qquad (1)$$

Here $NCF_{j,t}$ denotes the dollar monthly net cash flow for fund *j* during month *t*. $TNA_{j,t}$ refers to the total net assets at the end of month *t*, $R_{j,t}$ is the fund's return for month *t*. The estimate of net cash flow expressed in equation (1) implies that existing fund investors reinvest their dividend. In addition, the estimate assumes that all the new money is invested at the end of month. Further, we employ two portfolio-weighted approaches to calculate monthly performance for each type of new-money portfolios. The first one calculates equally-weighted new-money portfolios' returns. The second calculates cash flow-weighted returns using fund net cash flows, realized during the corresponding month, as weight.

We summarize the descriptive statistics for the new-money portfolios in Table 3.2. Thus, we report the statistics for equally-weighted and cash flow-weighted new money portfolios for each type of funds. For the purpose of comparison, we also show the returns on a TNA-weighted and an equally-weighted portfolio of all the funds in our sample. Thus, Panels A, B and C of the table report corresponding statistics for the samples of all funds, retail funds, and institutional funds respectively.

The table reports the mean, the median, the 25th and 75th percentile, and the standard deviation of monthly returns in excess of risk free rate, which in this case is a return on the one-month T-bill. In addition, the table shows the statistics for the excess return on the market portfolio, revealing that its average for our sample period was -0.10%. As one can note, the average returns on the positive cash flow portfolios are higher than the average returns on the negative cash flow portfolios. More specifically, the average excess return on the positive cash flow portfolio of retail funds (-0.08%) is 18 basis points higher than the average excess return on the negative cash flow portfolio of retail funds (-0.26%). Simultaneously, the average excess return on the positive cash flow portfolio of institutional funds is -0.10%, which is 11 basis points higher than the average excess return on the negative cash flow portfolio of institutional funds (-0.21%). Moreover, the level of excess return of the corresponding portfolios is fairly similar for both types of funds.

[Please insert Table 3.2 about here]

In line with previous "smart money" studies (see for example Gruber (1996), Zheng (1999), Sapp and Tiwari (2004), and Keswani and Stolin (2008)), we compute the risk-adjusted return of the portfolios using two approaches. First, following the "portfolio regression approach", we estimate time-series regression for the returns of each of the new-money portfolios. Next, we implement "fund regression approach". Fund regression approach estimates Fama-French's three-factor and Carhart's four-factor time-series regressions for each of the funds in our sample, and then computes the cross-sectional risk-adjusted return for each of the portfolios, month by month.

For the portfolio regression approach, for each month, we first measure the return of each of the portfolios as a weighted average of returns of the funds composing the portfolio. Then, to estimate the portfolio alpha, we regress monthly portfolio returns on factors of the corresponding model, specifying the following regressions:

$$R_{p,t} = \alpha_p^3 + \beta_{1,p} MKTRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \varepsilon_{pt,} \quad (2)$$

$$R_{p,t} = \alpha_p^4 + \beta_{1,p} MKTRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + \varepsilon_{pt}. \quad (3)$$

Here, $R_{p,t}$ is the monthly return on a portfolio of funds in excess of the one month T-bill return; $MKTRF_t$ is the excess return on a value-weighted market portfolio in month t; SMB_t is the return on the mimicking portfolio for the common size factor in stock returns in the month t; HML_t is the return on the mimicking portfolio for the common book-to-market equity factor in stock returns in the month *t*; UMD_t is the return on the mimicking portfolio for the one-year momentum in stock return factor in the month *t*; α_p are risk-adjusted returns or alphas from the corresponding factor model, and β are factor loadings of the corresponding factors.

For the fund regression approach, we first estimate alphas for each of the funds. Then, for each month, we calculate portfolio alpha as a weighted average of alphas of funds comprising the portfolio. Finally, we measure portfolio alpha averaging monthly portfolio alphas estimated in the previous stage. Thus, the regression equation for fund alphas, and the measure for the monthly estimated portfolio alpha can be expressed as the follows:

$$R_{jt} = \alpha_j^3 + \beta_{1,j}MKTRF_t + \beta_{2,j}SMB_t + \beta_{3,j}HML_t + \varepsilon_{jt}, \tag{4}$$

$$R_{jt} = \alpha_j^4 + \beta_{1,j}MKTRF_t + \beta_{2,j}SMB_t + \beta_{3,j}HML_t + \beta_{4,j}UMD_t + \varepsilon_{jt}, \tag{5}$$

$$\alpha_{pt} = \sum(\alpha_{jt} \times \omega_{jt}) / \sum \omega_{jt}, \tag{6}$$

where R_{jt} is the return , in month *t*, on a portfolio *j* in excess of the risk free rate, which is the return on the one month T-bill, α_{pt} is the excess return of the portfolio of mutual funds on factors of the corresponding model in month *t*, α_{jt} is the excess return of individual mutual funds on factors of the corresponding model in month *t*, and ω_{jt} is the portfolio weight of the individual fund *j* in month *t*.

In his work in 1997, Carhart demonstrates the superiority of the four-factor model – including the stock return momentum factor – to both the CAPM and Fama-French's three-factor model, in explaining cross-sectional variation in mutual fund returns. Implementing Carhart's four-factor model, Sapp and Tiwari (2004) show that inclusion of the momentum factor in the performance measurement eliminates the "smart money" effect. While in their more recent paper, Keswani and Stolin (2008), revisit the effect with U.K. data and subsequently with U.S. data on a monthly level, and report a robust "smart money" effect for the samples of both of the regions.

To test for fund selection ability on the part of investors of each fund type, we examine the difference between the alphas of the positive and negative cash flow portfolios of the corresponding fund sample. Thus, to compare "money smartness" of investors of retail and institutional funds, we compare the estimated differences.

Both – the portfolio regression approach and the fund regression approach – have their advantages and drawbacks. The portfolio regression approach is free of a look-ahead bias, which occurs when the fund is required to survive for a longer period of time in order to be included in the examination. That is since the approach requires mutual fund to have return information only one month after the portfolio formation. However, this approach does not account for time-variation in the portfolio compositions and their risk characteristics (see Zheng (1999), Fama and French (1996), Ferson and Harvey (1997)).

In contrast, the fund regression approach does suffer from a look-ahead bias, due to the existence of some new funds that do not have enough tracking history for the regression analysis. Requiring a minimum of 36 months of return data, to perform the time-series OLS estimation for each fund, we exclude some of the new funds and defunct funds included in the portfolio regression approach. The look-ahead bias may affect the precision of the new money performance measurement. At the same time, the fund regression approach captures the portfolio variations through time.

3.4 Performance of New Money Portfolios: Individual versus Institutional Investors

3.4.1 Portfolio Regression Approach

We start the analysis by reexamining investors' ability to gain superior returns based on their investment decisions. We conduct separate analysis for retail institutional fund samples. We report the results for the equally-weighted new money portfolios as reported in Panel A of Table 3.3. The first three rows of Panel A present the results of the analysis based on four-factor models for all funds, retail funds, and institutional funds respectively. The next three rows report corresponding results using the three-factor model.

[Please insert Table 3.3 about here]

For the three-factor model not accounting for momentum, the positive cash flow portfolios of both retail and institutional funds have statistically insignificant and negative alphas of -6.1 and -2.1 basis points per month respectively. Four-factor alphas are slightly lower for retail as well as for institutional funds (-7.1 and -2.8 basis points respectively). Thus, they are also negative and insignificant. At the same time, the average dollar invested in retail and institutional mutual funds, over the sample period, generated the insignificant four-factor alphas of -10.1 and -5.8 basis points respectively. Four-factor alphas of the negative cash flow portfolios are -13.1 basis points for retail funds and -9.2 basis points for institutional funds. Both of the estimates are statistically insignificant.

The reported difference in alphas represents returns generated by a trading strategy that is long in the positive cash flow portfolio, and short in the negative cash flow portfolio, estimates the fund selection ability of corresponding type of investors. The second column from the right presents the differences. The difference between the positive cash flow and negative cash portfolio alphas, for retail and institutional funds, are almost the same. For both models, the differences are positive and significant. Four-factor alpha difference for retail and institutional funds is equal to 6 and 6.4 basis points per month respectively, or to 72 and 76.8 annually. Therefore, the effect appears to be similar for both retail and institutional investors.

Furthermore, the results based on the three-factor model as well as those based on the four-factor model, show that alphas of positive cash flow portfolios of both types of investors are significantly higher than alphas of negative and average cash flow portfolios. This result indicates the existence of the smart money effect for investors of both types of funds. Notably, both models indicate that the alphas of institutional funds for all types of portfolios are about 4 basis points higher than those of retail portfolios.

The estimates for four-factor and three-factor alphas, reported in Panel A of Table 3.3, are lower than respective alpha estimates reported by Sapp and Tiwari (2004). For instance, in our sample, the four-factor alpha of all funds has a value of -6.2 basis points, which is merely 6 basis points lower than the four-factor alpha estimate reported by Sapp and Tiwari (2004). Correspondingly, the three-factor alpha of the positive cash flow portfolio of all funds in our sample equals -5.3, which is roughly 12 basis points lower than this reported by Zheng (1999) and Sapp and Tiwari (2004). One of the possible explanations for such disparity in alphas is a difference in the sample periods. Our sample period does not overlap the one used by Zheng, and has only two years in common with the sample period used by Sapp and Tiwari.

Panel A of Table 3.4 reports statistical estimates for the differences between alphas of positive, negative and average, equally-weighted cash flow portfolios, for different types of funds. For instance, the leftmost column from the top to the bottom respectively, shows the difference in alphas of positive portfolios for retail versus all, institutional versus all, institutional versus retail funds. For all types of portfolios, the alpha of institutional fund portfolios is significantly higher than that of retail fund portfolios.

[Please insert Table 3.4 about here]

We test the statistical significance of the difference in the observed smart money effect between investors of retail and institutional funds, and summarize the results in Panel A of Table 3.5. We note that there is no significant difference in the detected fund selection ability for the investors of retail and institutional funds.

[Please insert Table 3.5 about here]

To summarize, our results for equally-weighted new money portfolios confirm the existence of the smart money effect findings of Gruber (1996), Zheng (1999), and Keswani and Stolin (2008). In addition, these results support the findings of Keswani and Stolin arguing that implementation of monthly data allows detection of the smart money effect even controlling for the momentum factor. Furthermore, both types of investors display the “smart money” effect. Remarkably, the effect does not differ for investors of both retail and institutional funds.

Further, we take a look at the performance of cash flow-weighted new money portfolios. Panel B of Table 3.3 reports the results. Compared to the equal-weighting method, a cash flow-weighting scheme has the advantage of putting greater accent on funds having the larger absolute cash flows.

As can be seen, the alphas of positive, negative, and average portfolios for both types of funds, are negative, while for the positive portfolios, the alphas are not significantly different from zero. Moreover, the alphas are negative for both models excluding and including the momentum factor. Yet, the three-factor as well as four-factor alphas of positive cash flow portfolios of both types of funds are higher than alphas of corresponding negative and average cash flow portfolios. This result contradicts the findings of Sapp and Tiwari (2004), who report that the four-factor alpha of the average cash flow portfolio is higher than the corresponding alpha of the positive portfolio. It is possible that the difference in the result resides in the difference in the sample periods and data frequency. As documented by Keswani and Stolin (2008), even controlling for momentum, use of monthly flow data allows detection of the smart money effect, which is not observed with quarterly flow data, used in the Sapp and Tiwari (2004) study.

Our results show that the four-factor alpha of positive cash flow portfolio is not significantly different from zero and equal to -3.8 basis points per month for retail funds and -5.3 basis points per month for institutional funds. This is higher than the corresponding four-factor alphas of average portfolios, which are -8 basis points for retail funds and -10.3 basis points for institutional funds, and of negative portfolios, which equal -12.5 and -14.6 basis points for retail and institutional funds respectively. Thus, the results support the existence of fund selection ability for investors of both individual and institutional funds. Notably, in contrast to the results for the equally-weighted portfolios, the cash flow-weighted alphas of institutional funds are, though not significantly, lower than the corresponding alphas of retail funds (see Panel B of Table 3.4). This result might indicate a difference in the effect of fund size on net cash flows between retail and institutional funds, given that the cash flow-weighted measure gives much greater weight to the performance of the largest funds, which, in our sample, are associated with the highest in- and outflows.

Next, we examine the statistical significance of the observed smart money effect. For this purpose, we estimate the difference in alphas between the positive and the negative cash flow portfolios for each type of funds. A strategy of going short in the negative cash flow portfolio and long in the positive cash flow portfolio, generates a four-factor alpha of 8.7 basis points per month for retail funds and 9.3 basis points for institutional funds. While both of the alphas are economically significant, the institutional fund alpha is also statistically significant. At the same time, this strategy yields a three-factor alpha of 12.3 basis points per month for retail funds and 11.2 basis points per month for institutional funds.

Testing statistically the difference in the fund selection ability of investors of retail and institutional funds, we find that, compared to investors of retail funds, investors of institutional funds do not demonstrate significantly better fund selection ability (see Panel B of Table 3.5). Interestingly, the results of both equally-weighted and cash flow-weighted portfolio approaches, show that the smart money effect estimated, based on the four-factor model is, though insignificantly, stronger for the investors of institutional funds. Simultaneously, the effect is stronger for the investors of retail funds, if it is estimated using the three-factor model. This result indicates possible differences in the effect of momentum on flows of retail and institutional funds. Existence of such dissimilarity would be in line with the literature arguing that momentum follow behavioral varies for different types of investors (see, for example, Jegadeesh and Titman, (1993), Nofsinger and Sias (1999), Grinblatt and Keloharju (2001), Froot and Teo (2004), Sias (2004), Gallo, Phengpis and Swanson (2008)).

To summarize, the results for the cash flow-weighted portfolios corroborate with the equally-weighted portfolios findings, showing fund selection ability for the investors of both types of funds even controlling for stock return momentum, while revealing that investors of institutional funds do not exhibit superior fund selection ability.

3.4.2 Fund Regression Approach

Similarly to previous smart money studies (see Gruber (1996), Zheng (1999), Sapp and Tiwari (2004), Keswani and Stolin (2008), we also apply fund-regression approach to investigate the new cash flow performance.

Table 3.6 reports the portfolio three- and four-factor alphas from the fund regression approach for each type of investors as well as for all funds together. As we see, alphas obtained based on three-factor and four-factor models are economically and statistically significant, and negative, for both equally-weighted and cash flow-weighted approaches. This result holds for all types of portfolios and fund type combinations. For instance, the four-factor alpha of positive equally-weighted portfolio equals -27.9 basis points for retail funds and -28.6 basis points for institutional funds. The corresponding alphas, which were estimated based on cash flow-weighted approach, equal -11.8 and -21.7 basis points per month for retail and institutional funds respectively. The results indicating underperformance of actively managed mutual funds, with respect to the benchmark, are not too surprising, and are in line with a number of studies documenting relatively poor performance of the funds (see for example Jensen (1968), Gruber (1996), Fama and French (2008)). Yet, positive portfolio three- and four-factor alphas, for both equally-weighted and cash flow-weighted types of portfolios, are higher than the corresponding alphas of negative and average portfolios. Moreover, in all of the cases the difference between alphas of positive and negative, and positive and average portfolios is strongly economically and statistically significant. So, for example, the four-factor alpha of the positive cash flow-weighted flow portfolio is higher than that of the negative flow portfolio, at 27.7 basis points for retail funds and at 15.6 basis points higher for institutional funds, and the reported differences are significant at 1% level. Thus, these results confirm the results of previously described portfolio regression approach reporting fund selection ability for investors of both types of funds.

[Please insert Table 3.6 about here]

Next, we take a closer look at the differences in portfolio alphas between retail and institutional funds. Table 3.7 summarizes the discussed differences. We note that results based on equally-weighted portfolio technique are much more favorable to institutional investors than the results of cash flow-weighted approach. More specifically, while the four-factor alpha of the positive equally-weighted institutional portfolio is only 0.6 basis points lower than that of the corresponding retail portfolio, and the difference is statistically insignificant, the respective three-factor institutional portfolio alpha is 9.8 basis points lower than the retail portfolio one, and this difference is highly significant. As in the case of portfolio regression analysis illustrating the same tendency, this finding indicates possible difference in the effect of fund size on flows of retail and institutional funds. In addition, consistent with the portfolio regression approach results, four-factor model based results for both equally-weighted and cash flow-weighted approaches are, though slightly, more supportive for institutional fund investors than the results of the three-factor model. So, the four-factor alpha of negative cash-flow weighted portfolio of institutional funds is significantly higher than the corresponding alpha of retail funds' portfolio at 2.3 basis points per month, while the three-factor alpha of negative cash flow-weighted institutional portfolio is 1.9 basis points higher than this alpha of retail funds' portfolio, and the difference is not significant statistically. We suppose that previously mentioned differences in the effect of momentum on flows of the two types of funds can be one of possible explanations.

[Please insert Table 3.7 about here]

Finally, we estimate the difference in fund selection ability between investors of retail and institutional funds. To estimate this difference, we use the technique similar to the one employed in the portfolio regression analysis. We report the results of the analysis in Table 3.8. In contrast to the results of portfolio regression approach, the results indicate that investors of institutional funds representing the more sophisticated investors display weaker fund selection ability compared to investors of retail investors. In particular, a hypothetical strategy of going short in the negative cash flow-weighted portfolio of retail funds and long in the positive cash flow-weighted portfolio of retail funds, generates four-factor alpha of 12.1 basis points per month higher compared to the equivalent strategy applied to institutional funds' portfolios. So, to reiterate, implementation of the fund regression approach implies much stronger survivorship conditions than these sufficient for portfolio regression approach. Thus, as previously discussed in this chapter, fund regression approach suffers from the look-ahead bias. Presumably, the stronger the effect of such fund characteristics as fund age and fund size, the stronger the look-ahead bias. At the same time, as we noted before, size effect might be different for retail and institutional funds. More specifically, both relative portfolio performance of institutional funds and relative fund selection ability of institutional investors, with respect to those of retail funds and retail investors respectively, are weaker if calculated based on the approach, putting greater weight on the largest funds. Furthermore, the look-ahead bias can be expected to have a stronger effect on the estimates of institutional funds, negatively affecting the estimates.

[Please insert Table 3.8 about here]

Therefore, the results for the fund regression approach support our findings for the portfolio regression approach and show that investors of both retail and institutional funds exhibit fund selection ability. While keeping in mind the possible effect of look-ahead bias attributing the fund regression approach, and described above, we conclude that investors of institutional funds do not exhibit superior fund selection ability, while investors of retail funds demonstrate a comparable, or even stronger, smart money effect.

3.4.3 Small versus Large Funds

Zheng (1999) reports that the smart money effect is mainly caused by investment flows into and out of small mutual funds. Zheng suggests that great cautiousness by investors, when investing in small funds rather than in large funds, is one of the potential reasons for the observed disparity. However, fund-size sensitivity can differ for investors of retail and institutional funds. Retail fund investors might care more for investing in small funds, due to relatively high search costs and limited diversification options. In order to detect potential differences, we reexamine the discussed size effect separately for investors of retail and institutional funds. For this purpose, we estimate performance of the new money portfolios, for each fund type separately, for funds representing the smallest 25 percentile and the largest 25 percentile, based on fund TNA of the corresponding month.

The results are reported in Table 3.9. Consistent with Zheng's (1999) findings, our results show that, for investors of both types of funds, small funds demonstrate a much stronger smart money effect, while large funds do not display any significant smart money effect at all. Only in small funds do positive portfolios significantly outperform negative portfolios. For both types of funds, the greatest difference between positive and negative portfolios is detected in cash flow-weighted portfolios. Interestingly, for retail funds, a statistically significant difference between alphas of positive and negative portfolios attributes only cash flow-weighted portfolios. In contrast, for institutional funds, a significant difference is found only in equally-weighted portfolios. Moreover, the cash flow-weighted portfolio based strategy, of going short in the negative portfolio and long in the positive one, generates roughly 16 basis points per month higher four-factor and three-factor alphas for retail funds than for institutional funds. Simultaneously, a similar strategy, based on equally-weighted portfolios, generates approximately 6 basis points more for institutional funds than for retail. More specifically, a strategy of going short in the negative cash flow-weighted portfolio and long in the positive cash flow-weighted portfolio of retail funds, generates a significant four-factor alpha of 30.6 basis points per month, while for institutional funds it would gain an insignificant four-factor alpha of 14.4 basis points. At the same time, the corresponding strategy, based on equally-weighted portfolios, yields an insignificant four-factor alpha of 2 basis points per month for retail funds, while yielding a significant alpha of 8.2 basis points for institutional funds. The observed asymmetries in strategy effectiveness, indicate differences between investors of the two types of funds in the smart money size effect. Cash flow-weighted based results indicate that a higher proportion of retail fund investors' money flows exhibit the smart money effect. Moreover, the effect is economically, though insignificantly, higher than demonstrated by investors of institutional funds. Alternatively, significant equally-weighted portfolio based results demonstrated by institutional flows imply that investors of institutional funds would rather use their diversification advantage, investing equally in several funds which will outperform as a group. This asymmetry is in line with the hypothesis that, when investing in small funds, individual investors are more cautious than institutional investors.

[Please insert Table 3.9 about here]

To summarize, in line with the results of Zheng (1999), we find that the smart money effect is mainly a result of small funds' investment flows. Moreover, our results indicate that the observed size effect differs for retail and institutional funds. As said: it appears that individual investors are more cautious when investing in small funds than institutional investors are. Possibly, higher search costs together with relatively limited diversification options, cause individual investors to be more careful when investing in small funds.

3.4.4 Expansion versus Recession Periods

A number of studies document that mutual fund performance varies over business cycles (Moskowitz (2000), Kosowski (2006)). Moskowitz (2000) finds that mutual funds significantly outperform the market during recession periods. In a more recent study, Kosowski (2006) reports a similar pattern. The author shows that over recession periods mutual funds generate up to 5 percent more alpha per year than over expansion periods. Thus, return variation across business cycles makes the opportunity of investing in mutual funds qualitatively different for recessionary and non-recessionary periods. Alternatively, superior fund manager skills are found to be more pronounced over recession periods (Avramov and Wermers (2006)). If investors realize the existence of this tendency, they should demonstrate a stronger fund selection ability over recession periods.

To test this question, we re-estimate the smart money effect for recession and expansion periods. More specifically, for investors of each type of fund, we compare the performance of positive and negative new money portfolios separately, for recession and expansion periods, using the NBER recession – expansion classification (see Appendix 3.1). There are two expansion and two recession periods in the sample period. In total, there are 26 recession and 98 expansion months.

Table 3.10 reports the results of the analysis. Notably, both types of investor demonstrate the smart money effect in expansion periods, while they do not show a significant smart money effect over recession periods. In particular, over expansion periods, the three-factor alpha of positive cash flow-weighted portfolio is 23.4 and 21.3 basis points per month higher than the alpha of negative cash flow-weighted portfolio for retail and institutional funds. In contrast, over recession periods, the equivalent positive portfolio, although insignificantly, underperforms the portfolio of negative cash flow at 10.4 and 9 basis points per month correspondingly for retail and institutional funds.

[Please insert Table 3.10 about here]

Thereby, our results reveal that, neither investors of retail funds nor supposedly more sophisticated investors of institutional funds, benefit from higher predictability of managerial skills and superior fund performance over recession periods. In contrast, investors of both types of fund demonstrate no significant selection ability over recessions. Potentially, difference in investment patterns characterizing recession and expansion periods is one of the explanations for the observed result.

Interestingly, for investors of both fund types, the expansion smart money effect weakens after controlling for momentum, while the recession smart money effect appears to be stronger after controlling for momentum. This result might indicate that flows-momentum relationship differs over business cycles.

3.4.5 Robustness Issues

All the previously reported analyses are based on the sample in which we do not distinguish between retail funds composing the same portfolio with institutional "peers", and those that do not have such peers, and vice versa: institutional funds having retail peers versus institutional funds without retail peers. While one could argue that investors of retail funds compared with investors of institutional funds initially have different investment opportunities, since the set of available portfolios is not the same for investors of retail and institutional funds. If the opportunity sets are not equal in terms of return characteristics, comparison of fund selection abilities for investors of the two types of fund, without controlling for the differences in opportunity sets, could yield distorted results. To address this issue, we repeat the analysis including only funds with peers, targeting opposite investor types. All the results and main conclusions remain the same.

For additional robustness tests, we redo the analysis using normalized cash flows, and controlling for different style classifications. Furthermore, we repeat the analysis using appraisal ratio of the new cash flow portfolios to measure the "smart money" effect.[29] We confirm that the results of all of the mentioned above robustness tests stay qualitatively the same.[30]

3.5 Determinants of Cash Flows: Retail versus Institutional Mutual Funds

[29] In particular, instead of the explained and implemented earlier in this chapter comparison of risk-adjust and unadjusted return measures of new cash flow portfolios, we estimate and compare appraisal ratios of the corresponding new cash flow portfolios. Similarly to the methodology using fund risk-adjusted and unadjusted performance measures, the approach employing appraisal ratio implies existence of the "smart money" effect if the appraisal ratio of the positive net cash flow portfolio is significantly higher than this ratio of the negative net cash flow portfolio.
[30] Results of the robustness tests will be provided by authors upon request.

So far, consistent with previous studies investigating the smart money effect, our results indicate that investors in our sample exhibit an ability to select funds, and these results hold, even controlling for momentum exposure. Furthermore, we find that investors of both retail and institutional funds demonstrate a fund selection ability, and this ability is not stronger for investors of institutional funds. In addition, the results detect a few signs of possible differences in the way investors of the two types of funds make their investment or divestment decisions. So, fund size and momentum exposure appear to have a different effect on flows of retail versus institutional funds.

Thus, next, we examine the influence of fund size and stock return momentum on cash flows of each type of funds. In addition, we control for several other factors documented by the literature as affecting investment flows such as past performance, fund risk, flows into investment objective category (IOC) to which the fund belongs, portfolio turnover, expense ratio, and fund age (see, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), Del Guercio and Tkac (2002)). We run a pooled OLS regression with the fund's monthly net cash flows as dependent variable. The main explanatory variables are the fund total net assets estimated at the end of the previous month, and the fund's momentum (UMD) factor loading obtained from a four-factor model-based rolling regression over the previous 36 months of fund performance. As mentioned above, we also control for fund lagged performance, risk, age, expense and turnover ratios, and the flows into fund's IOC.

Following Del Guercio and Tkac's (2002) methodology, we also include a set of time-style interaction variables, one for each combination of month and style. For instance, G200202 variable takes value one if this observation relates to growth style fund in February 2002, and zero otherwise. The time component of the interaction dummy variable captures any cross-sectional correlations in the observations which could emerge due to differences in average flows across months of the sample. The style component accounts to the fact that in any given month, funds with different IOCs may experience average flows that are significantly different from these of other styles. Thereby, adding a time-style interaction dummy reduces the above explained sources of residual dependence, increasing precision of the estimates. Furthermore, to correct for heteroskedasticity, we cluster standard errors by funds. To estimate the corresponding coefficients for investors of institutional and retail funds separately, we interact each of the performance and non-performance explanatory variables with fund type dummy variables. In particular, we include both sets of interactions: the interaction of each of the explanatory variables with the retail fund dummy, which gets value one if an observation relates to flows of retail funds and zero otherwise, and the interaction with the institutional fund dummy, getting value one if an observation is related to an institutional fund.

To estimate the difference in effect of each of those variables on flows between retail and institutional funds, we specify separate regression including set of explanatory variables with and without interaction with the institutional fund dummy. Thus, the coefficients of the variables with the interaction represent the difference in effect of corresponding variable on flows of institutional versus retail funds, and t-statistics of those coefficients reflect statistical significance of the differences.

Table 3.11 reports the results. Specification (1) in Panel A of Table 3.11 reports results for all funds in our sample. Specification (2) in Panel B summarizes estimates of regression specification including fund type interactions terms. The last column in the table reports differences between coefficients of the corresponding variable of institutional versus retail funds.

We see that, while flows of both retail and institutional funds exhibit a significant and positive relationship with momentum loading, the relationship is stronger for institutional funds. Thus, the results of Panel B indicate that, increase of factor loading in one unit, predicts, for institutional funds, two-thirds higher additional inflows than for a retail fund. This result suggests that institutional funds' investors exhibit much stronger momentum following behavior than investors of retail funds. This finding is in line with the earlier results indicating differences between investors of retail and institutional funds in the influence of momentum on the smart money effect. Furthermore, it supports evidence of momentum following behavior of institutional investors documented by prior studies (see, for example, Jegadeesh and Titman, (1993), Nofsinger and Sias (1999), Grinblatt and Keloharju (2001), Froot and Teo (2004), Sias (2004), Gallo, Phengpis and Swanson (2008)). In addition, the results reveal that fund size does not have the same effect on flows of retail and institutional funds. Large institutional funds attract significantly higher cash flows than their smaller competitors. In contrast, we do not find any significant effect of size on flows of retail funds. This result confirms the difference in fund size-flow relationship between retail and institutional funds detected by the previous analyses. The reason for this difference is worthy of further investigation.

[Please insert Table 3.11 about here]

Therefore, the results show that investors of both types of fund exhibit momentum following behavior, while this behavior is much more pronounced among investors of institutional funds. In addition, we find that fund size has an effect only on flows of institutional funds. While it appears to be positively correlated with flows of institutional funds, fund size-flow relationship for retail funds is found to be economically and statistically insignificant.

3.6 Summary and Conclusion

In this chapter we reexamine the smart money effect, comparing the fund selection ability of investors of retail funds, representing mostly unsophisticated individual investors, against this ability of investors of institutional funds, among whom – though a higher proportion represents sophisticated investors – are also disadvantaged investors due to account restriction or tax issues.

We explore this question by examining the smart money effect separately for investors of retail and institutional funds. We use the complete universe of diversified U.S. equity mutual funds for the period January 1999 to May 2009 in the CRSP Survivor-Bias Free U.S. Mutual Fund Database. We use CRSP's classification of institutional and retail funds to identify fund type.

Note that this classification may not be a precise identifier of investor type. For instance, the final investment decision of 401k plans' participants is taken by an individual investor, while their capital flows may combine flows of either an institutional or a retail fund. Nevertheless, it seems reasonable to assume that the classification of funds into retail and institutional implies differences in investor composition of the two types of fund. In particular, the overwhelming majority of retail fund investors apparently are regular individuals. At the same time, institutional investors, if participating in mutual funds, can be expected to invest in institutional funds. Furthermore, presumably more sophisticated institutional investors influence flows of institutional funds, while flows of retail funds are determined by investment decisions of unsophisticated – individual investors.

Following the methodology employed by previous smart money studies, at the beginning of each month and for each type of fund, we construct two portfolios of new-money. The first portfolio consists of all funds with a positive net cash flow realized during the previous month. The second portfolio comprises all funds with a negative net cash flow realized over the same month. Next, we estimate the performance of each of the portfolios in the subsequent month using both the Fama-French's (1993) model and the Carhart's (1997) model including a momentum factor.

To test for fund selection ability on the part of investors of each fund type, we examine the difference between the alphas of the positive and negative cash flow portfolios of the corresponding fund sample. Thus, to compare money smartness of investors of retail and institutional funds, we compare the estimated differences.

In line with the studies of Gruber (1996), Zheng (1999), and Keswani and Stolin (2008), we find a smart money effect for investors of both retail and institutional mutual funds. The effect is robust to different measures of performance and flows, and controlling for stock return momentum and investment style. Consistent with the findings of Zheng (1999), we find that the smart money effect comes mainly from small funds. We also observe that investors of both types of funds demonstrate better fund selection ability over expansion periods than during recession periods.

Surprisingly, our results suggest that investors of institutional funds, with a higher representation of more sophisticated investors, do not demonstrate a better fund selection ability. Probably, performance persistence, widely documented by existing mutual fund literature, represents one of the main observable attributes of superior ability of the fund manager, while past return information is accessible and widely used by investors of both types of funds. If so, a higher level of financial sophistication does not necessarily lead to better fund selection ability. Alternatively, performance persistence, providing some extent of return predictability, together with accessibility of past return records and financial advisers' services, allow unsophisticated investors to demonstrate fund selection ability as well.

Concurrently, our results indicate dissimilarities in the cash flow development for retail and institutional funds. The observed dissimilarities can be a result of difference in investment decision patterns characterizing investors of each fund type, and deserve further investigation.

3.7 Tables, Figures, and Appendix (Chapter 3)

Table 3.1
Descriptive Statistics for Mutual Fund Sample

The table presents summary statistics on the mutual fund sample obtained from the CRSP Survivor-Bias Free US Mutual Fund Database. The sample includes all U.S. equity mutual funds that existed at any time during January 1999 to May 2009 for which monthly total net assets (TNA) values are available. We exclude sector funds, international funds, specialized funds, and balanced funds. Panel A reports corresponding statistics for the entire sample. Panel B reports corresponding statistics for the sample of retail fund investors' mutual funds. Panel C reports corresponding statistics for the sample of institutional fund investors' mutual funds. The final sample of all funds consists of 11,710 fund-entities comprising 818,530 fund-months, the sample of retail funds consists of 7,779 fund-entities comprising 577,648 fund-months, the sample of institutional funds consists of 3,931 fund-entities comprising 240,881fund-months. The dollar monthly net cash flow ($NCF_{j,t}$) for fund j during month t is measured as $NCF_{j,t} = TNA_{j,t} - TNA_{j,t-1} \times (1 + R_{j,t})$. In this equation, the terms $TNA_{j,t-1}$ and $TNA_{j,t}$ represent the total net assets for the fund at the end of month $t-1$ and t respectively, $R_{j,t}$ represents the fund's return in month t. The normalized quarterly cash flow for a fund during a month is computed as the dollar monthly cash flow for the fund divided by the TNA at the beginning of the month. Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA, maximum front-end load is the maximum percent charges applied at the time of purchase, and expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. For each item, we first compute the cross-sectional averages in each year from 1999 to 2009. The reported statistics are computed from the time series of the 11 annual cross-sectional average figures for each item.

	Mean	Median	25th percentile	75th percentile	St. Dev
Panel A: All Funds					
Monthly Return (%)	0.14	0.09	-1.37	1.64	2.48
Monthly Normalized Cash Flow	1.96	-0.06	-1.79	2.67	12.01
Monthly Net Cash Flow (mill $)	0.88	0.01	-0.62	0.63	23.96
Monthly TNA (mill $)	431.84	28.39	4.16	154.95	2571.39
Turnover Ratio (% year)	76.47	65.68	34.66	107.98	52.84
Maximum Front-End Load Fee (%)	3.30	4.56	0.51	5.30	2.29
Expense Ratio (% year)	1.45	1.40	1.04	1.91	0.56
Panel B: Retail Investors' funds					
Monthly Return (%)	0.13	0.08	-1.40	1.64	2.52
Monthly Normalized Cash Flow	1.82	-0.21	-1.87	2.46	11.52
Monthly Net Cash Flow (mill $)	0.44	-0.02	-0.81	0.58	24.09
Monthly TNA (mill $)	505.05	29.15	4.84	160.72	2952.69
Turnover Ratio (% year)	76.37	65.32	34.50	107.65	53.13
Maximum Front-End Load Fee (%)	3.40	4.64	0.75	5.36	2.24
Expense Ratio (% year)	1.62	1.61	1.23	2.04	0.53
Panel C: Institutional Investors' Funds					
Monthly Return (%)	0.18	0.13	-1.29	1.65	2.36
Monthly Normalized Cash Flow	2.13	0.25	-1.59	3.06	12.82
Monthly Net Cash Flow (mill $)	1.73	0.01	-0.30	0.85	22.94
Monthly TNA (mill $)	247.02	27.24	2.97	144.12	1134.27
Turnover Ratio (% year)	76.91	66.81	35.01	109.22	52.28
Maximum Front-End Load Fee (%)	1.50	0.32	0.00	3.53	1.76
Expense Ratio (% year)	1.02	1.00	0.78	1.24	0.39

Table 3.2
Descriptive Statistics for Mutual Fund Portfolio Excess Returns

This table presents summary statistics for monthly returns in excess of the risk-free rate on portfolios of mutual funds for the period January 1999 to May 2009. Panel A reports corresponding statistics for the entire sample. Panel B reports corresponding statistics for the sample of retail investors' mutual funds. Panel C reports corresponding statistics for the sample of institutional investors' mutual funds. The first row of each panel gives statistics for a TNA-weighted portfolio of all funds in the sample. The second row describes an equally-weighted portfolio of all funds in the sample. Also shown are the summary statistics for portfolios formed on the basis of monthly net new cash flows. Each month funds are grouped into either the positive cash flow portfolio or the negative cash flow portfolio based on the sign of the net cash flow experienced by each fund during the previous month. These portfolios are either equally-weighted across funds or cash flow-weighted, and are rebalanced monthly. Summary statistics are also given for the market factor, labeled MKTRF. MKTRF and RF represents the excess return on the market portfolio and risk-free rate as reported by CRSP. Returns are expressed in percent per month.

	Mean	Median	25th percentile	75th percentile	St. Dev
Panel A: All Funds					
TNA-weighted average fund portfolio	-0.190	0.612	-2.530	3.135	4.793
Equally-weighted average fund portfolio	-0.134	0.656	-2.925	3.183	4.899
Equally-weighted negative cash flow portfolio	-0.184	0.612	-2.760	3.172	4.870
Equally-weighted positive cash flow portfolio	-0.092	0.689	-2.765	3.262	4.947
Cash Flow-weighted negative cash flow portfolio	-0.252	0.446	-2.875	3.056	4.855
Cash Flow-weighted positive cash flow portfolio	-0.087	0.725	-2.583	3.131	4.940
Panel B: Retail Investors' funds					
TNA-weighted average fund portfolio	-0.187	0.590	-2.499	3.141	4.790
Equally-weighted average fund portfolio	-0.148	0.634	-2.936	3.161	4.882
Equally-weighted negative cash flow portfolio	-0.199	0.586	-2.749	3.134	4.868
Equally-weighted positive cash flow portfolio	-0.103	0.705	-2.742	3.247	4.907
Cash Flow-weighted negative cash flow portfolio	-0.259	0.409	-2.845	3.087	4.868
Cash Flow-weighted positive cash flow portfolio	-0.075	0.686	-2.660	3.141	4.901
Panel C: Institutional Investors' Funds					
TNA-weighted average fund portfolio	-0.188	0.656	-2.654	2.976	4.793
Equally-weighted average fund portfolio	-0.094	0.672	-2.859	3.258	4.931
Equally-weighted negative cash flow portfolio	-0.137	0.665	-2.761	3.249	4.869
Equally-weighted positive cash flow portfolio	-0.057	0.659	-2.813	3.347	5.006
Cash Flow-weighted negative cash flow portfolio	-0.211	0.499	-2.790	2.865	4.797
Cash Flow-weighted positive cash flow portfolio	-0.103	0.672	-2.712	3.271	4.933
Market factor (MKTRF)	-0.102	0.770	-2.500	3.360	4.887
Monthly risk-free rate (RF)	0.254	0.240	0.120	0.400	0.151

Table 3.3

Performance of New Money Estimated by Risk-Adjusted Returns Using the Portfolio Regression Approach Equally-weighted portfolios

For each sample, each month from January 1999 to May 2009, mutual funds are grouped into either the positive cash flow portfolio or the negative cash flow portfolio based on the sign of the net cash flow experienced by each fund during the previous month. Portfolio performance is evaluated based on the estimated portfolio alpha. The four-factor portfolio alpha is calculated as the intercept from the monthly time series regression of portfolio excess returns on the market excess return (MKTRF) and mimicking portfolios for size (SMB), book-to-market (HML), and momentum (UMD) factors (MKTRF, SMB, HML, UMD are obtained from CRSP): $r_{p,t} = \alpha_p + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + e_{pt}$. The three-factor alpha is based on a model that excludes the momentum factor. The table reports estimates of portfolio alphas and factor loadings for the new money portfolios formed using equally-weighted fund returns (Panel A), and cash flow-weighted fund returns (Panel B). Estimates are also presented for an average fund portfolio that is equally-weighted in all available funds (Panel A), and the TNA-weighted portfolio of all available funds (Panel B). The table also reports the difference in alphas between (a) the positive cash flow portfolio and the negative cash flow portfolio, and (b) the positive cash flow and the average portfolio. Alphas are reported as percent per month. The *t*-statistics based on the Newey-West covariance matrix are reported in parenthesis. Statistical significance is denoted only for alphas. * Significant at 10% level. ** Significant at 5% level.

Panel A: Equally-weighted portfolios

	Positive Cash Flow Portfolio					Negative Cash Flow Portfolio					Average Portfolio						
	Alpha	MKTRF	SMB	HML	UMD	Alpha	MKTRF	SMB	HML	UMD	Alpha	MKTRF	SMB	HML	UMD	Posit. vs. Negat.	Posit. vs. Aver.
Four factor model																	
All funds	-0.062	0.996	0.134	0.047	0.034	-0.122	0.967	0.061	0.099	-0.030	-0.091	0.983	0.103	0.070	0.004	0.060**	0.029**
	(-1.00)	(85.59)	(5.85)	(1.74)	(4.82)	(-1.59)	(55.84)	(1.84)	(2.39)	(-1.76)	(-1.35)	(72.87)	(4.08)	(2.19)	(0.58)	(2.13)	(2.29)
Retail funds	-0.071	0.999	0.131	0.049	0.049	-0.131	0.964	0.057	0.093	-0.033	-0.101	0.979	0.101	0.063	0.004	0.060*	0.030**
	(-1.20)	(83.97)	(5.75)	(1.42)	(5.57)	(-1.64)	(53.08)	(1.71)	(2.13)	(-1.82)	(-1.49)	(69.88)	(4.09)	(1.91)	(0.58)	(1.89)	2.09)
Instit. funds	-0.028	1.006	0.133	0.060	0.026	-0.092	0.976	0.071	0.121	-0.020	-0.058	0.992	0.104	0.090	0.005	0.064**	0.030**
	(-0.38)	(72.41)	(5.24)	(2.04)	(3.95)	(-1.36)	(64.16)	(2.22)	(3.22)	(-1.44)	(-0.86)	(73.57)	(3.78)	(2.73)	(0.61)	(2.26)	(2.13)
Three factor model																	
All funds	-0.053	0.973	0.144	0.036		-0.130*	0.987	0.052	0.109		-0.089	0.980	0.104	0.069		0.077*	0.036*
	(-0.80)	(97.8)	(6.26)	(1.13)		(-1.74)	(50.72)	(1.47)	(2.39)		(-1.34)	(74.74)	(4.027)	(2.093)		(1.71)	1.73)
Retail funds	-0.061	0.963	0.142	0.027		-0.139*	0.986	0.047	0.103		-0.100	0.976	0.103*	0.061*		0.078*	0.038*
	(-0.94)	(92.49)	(6.09)	(0.79)		(-1.79)	(46.9)	(1.33)	(2.15)		(-1.49)	(71.77)	(4.05)	(1.82)		(1.66)	1.70)
Instit. funds	-0.021	0.989	0.140	0.052		-0.097	0.989	0.065	0.127		-0.057	0.989	0.106	0.088		0.075*	0.036
	(-0.28)	(78.51)	(5.61)	(1.61)		(-1.48)	(65.22)	(1.9)	(3.16)		(-0.85)	(73.19)	(3.74)	(2.61)		(1.68)	(1.60)

Panel B: Cash flow-weighted portfolios																	
	Positive Cash Flow Portfolio					Negative Cash Flow Portfolio					Average Portfolio						
	Alpha	MKTRF	SMB	HML	UMD	Alpha	MKTRF	SMB	HML	UMD	Alpha	MKTRF	SMB	HML	UMD	Posit. vs. Negat.	Posit. vs. Aver.
Four factor model																	
All funds	-0.052	0.992	0.146	-0.012	0.075	-0.133*	0.964	-0.023	0.085	-0.053	-0.087**	0.979	0.026	0.022	0.009	0.081	0.035
	(-1.52)	(108.6)	(6.90	(-0.47)	(5.65)	(-1.81)	(52.02)	(-0.67)	(2.20)	(-2.86)	(-2.22)	(102.8)	(2.17)	(1.29)	(1.59)	(1.36)	(1.32)
Retail funds	-0.038	0.981	0.147	-0.029	0.088	-0.125	0.963	-0.036	0.067	-0.057	-0.080*	0.978	0.024	0.012	0.012	0.087	0.042
	(-0.95)	(101.4)	(5.85)	(-1.00)	(5.81)	(-1.58)	(49.63)	(-1.05)	(1.69)	(-2.95)	(-1.92)	(101.4)	(2.26)	(0.61)	(1.76)	(1.34)	(1.59)
Instit. funds	-0.0531	0.995	0.115	0.0227	0.037	-0.146**	0.963	0.026	0.140	-0.038	-0.103***	0.978	0.029	0.068	-0.005	0.093**	0.050*
	(-1.63)	(140.2)	(7.01)	(1.18)	(6.30)	(-2.54)	(58.8)	(0.81)	(4.11)	(-2.56)	(-3.85)	(87.55)	(1.47)	(3.56)	(-0.95)	(2.18)	(1.78)
Three-factor model																	
All funds	-0.033	0.942	0.168	-0.036		-0.147**	1.000	-0.038	0.103		-0.085**	0.973	0.029	0.019		0.114	0.052
	(-0.55)	(75.34)	(6.85)	(-0.83)		(-2.01)	(45.52	(-1.01)	(2.31)		(-2.17)	(147.5)	(2.41)	(1.12)		(1.28)	(1.03)
Retail funds	-0.016	0.923	0.172	0.058		-0.139*	1.001	-0.053	0.088		-0.078*	0.970	0.028	0.008		0.123	0.061
	(-0.24)	(69.22)	(5.70)	(-1.12)		(-1.76)	(43.27)	(-1.37)	(1.86)		(-1.85)	(158.8)	(2.58)	(0.42)		(1.27)	(1.16)
Instit. funds	-0.044	0.971	0.125	0.011		-0.156***	0.988	0.015	0.153		-0.104***	0.982	0.027	0.070		0.112*	0.060
	(-1.01)	(142.5)	(7.35)	(0.41)		(-2.74)	(56.32)	(0.43)	(4.16)		(-3.96)	(85.4)	(1.32)	(3.55)		(1.84)	(1.41)

Table 3.4
Portfolio Regression Approach: Mean Difference in Alphas between portfolios of different fund types

The table reports the statistical estimates for the differences between alphas of positive, negative, and average portfolios for different types of funds. Portfolio alphas are estimated using portfolio regression approach. Panel A reports the differences for alphas measured based on equally-weighted cash flow portfolio method. For instance, the first column from the left shows from the top to the bottom the difference in alphas of positive portfolios for retail versus all, institutional versus all, institutional versus retail funds respectively. Panel B reports corresponding differences for alphas measured based on cash flow-weighted portfolio method. The *t*-statistics in parentheses test whether the alpha difference between the portfolios is significantly different from zero. The *t*-statistics is based on the Newey-West covariance matrix. Differences are reported in percentage per month. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Panel A: Equally-weighted portfolios						Panel B: Cash flow-weighted portfolios					
	Four factor model			Three-factor model			Four factor model			Three-factor model		
	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio
Difference in Alphas Retail vs. All	-0.009*	-0.009***	-0.01***	-0.008	-0.010***	-0.010***	0.014	0.008	0.007*	0.017	0.007	0.007**
	(-1.77)	(-2.63)	(-6.17)	(-1.62)	(-2.91)	(-6.24)	(1.03)	(1.18)	(1.89)	(1.22)	(0.92)	(2.14)
Difference in Alphas Institutional vs. All	0.034*	0.031***	0.032***	0.032*	0.033***	0.032***	-0.001	-0.013	-0.016	-0.011	-0.009	-0.02
	(1.93)	(2.9)	(5.17)	(1.95)	(3.21)	(5.17)	(-0.05)	(-0.58)	(-0.95)	(-0.37)	(-0.41)	(-1.02)
Difference in Alphas Institutional vs. Retail	0.043*	0.039***	0.042***	0.040*	0.043***	0.043***	-0.015	-0.022	-0.023	-0.028	-0.017	-0.027
	(1.9)	(2.85)	(5.5)	(1.9)	(3.15)	(5.5)	(-0.40)	(-0.72)	(-1.13)	(-0.66)	(-0.54)	(-1.20)

Table 3.5

Portfolio Regression Approach: Mean Difference in (Alpha of Positive Portfolio - Alpha of Negative Portfolio), and in (Alpha of Positive Portfolio - Alpha of Average Portfolio) for different fund types

The table reports the statistical estimates for the differences between each two types of funds in alpha difference of positive versus negative, and positive versus average portfolios. Portfolio alphas are estimated using portfolio regression approach. Panel A reports the differences for alphas measured based on equally-weighted cash flow portfolio method. For instance, the first column from the left shows from the top to the bottom respectively the difference between retail versus all, institutional versus all, and institutional versus retail funds in alpha difference of positive versus negative portfolios. Panel B reports corresponding differences for alphas measured based on cash flow-weighted portfolio method. The *t*-statistics in parentheses test whether the difference is significantly different from zero. The *t*-statistics is based on the Newey-West covariance matrix. Differences are reported in percentage per month. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Panel A: Equally-weighted portfolios				Panel B: Cash flow-weighted portfolios			
	Four factor model		Three-factor model		Four factor model		Three-factor model	
	Positive vs. Negative	Positive vs. Average	Positive vs. Negative	Positive vs. Average	Positive vs. Negative	Positive vs. Average	Positive vs. Negative	Positive vs. Average
Difference in "VS" Alphas Retail vs. All	-0.001	0.001	0.001	0.002	0.006	0.007	0.010	0.010
	(-0.02)	(0.32)	(0.22)	(0.47)	(0.37)	(0.55)	(0.51)	(0.64)
Difference in "VS" Alphas Institutional vs. All	0.003	0.002	-0.001	-0.001	0.012	0.015	-0.001	0.009
	(0.16)	(0.17)	(-0.05)	(-0.05)	(0.30)	(0.61)	(-0.03)	(0.29)
Difference in "VS" Alphas Institutional vs. Retail	0.003	0.001	-0.003	-0.003	0.007	0.008	-0. 011	-0.001
	(0.13)	(0.04)	(-0.09)	(-0.19)	(0.12)	(0.22)	(-0.16)	(-0.03)

Table 3.6

Performance of New Money Estimated by Risk-Adjusted Returns Using the Fund Regression Approach

Each month from January 1999 to May 2009, mutual funds are grouped into either the positive cash flow portfolio or the negative cash flow portfolio based on the sign of the net cash flow experienced by each fund during the previous month. The four-factor portfolio alpha is calculated as the weighted average of the realized alphas of the individual funds obtained from the time-series regression of fund excess returns on the market excess return (MKTRF) and mimicking portfolios for size (SMB), book-to-market (HML), and momentum (UMD) factors (MKTRF, SMB, HML, UMD are obtained from CRSP): $r_{j,t} = \alpha_j + \beta_{j,MKTRF}MKTRF_t + \beta_{j,SMB}SMB_t + \beta_{j,HML}HML_t + \beta_{j,UMD}UMD_t + e_{j,t}$. The three-factor alpha is based on a model that excludes the momentum factor. Panel A of the table reports estimates of portfolio alphas and factor loadings for the new money portfolios formed using equally-weighted fund alphas. Estimates are also presented for an average fund portfolio that is equally-weighted in all available funds. Panel B reports estimates for the new money portfolios formed using cash flow-weighted fund alphas. Estimates are also presented for an average fund portfolio representing the TNA-weighted portfolio of all available funds. The table also reports the difference in alphas between (a) the positive cash flow portfolio and the negative cash flow portfolio, and (b) the positive cash flow and the average portfolio. Alphas are reported as percent per month. The *t*-statistics based on the Newey-West covariance matrix are reported in parenthesis. Statistical significance is denoted only for alphas. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Panel A: Equally-weighted portfolios

	Four factor model					Three-factor model				
	Alpha			Difference in Alphas		Alpha			Difference in Alphas	
	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive. vs. Negative	Positive vs. Average	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive vs. Negative	Positive vs. Average
All funds	-0.281***	-0.426***	-0.366***	0.146***	0.085***	-0.279***	-0.429***	-0.367***	0.150***	0.088***
	(-14.73)	(-21.43)	(-20.13)	(6.65)	(8.57)	(-18.74)	(-23.44)	(-23.79)	(8.94)	(12.94)
Retail funds	-0.279***	-0.438***	-0.377***	0.159***	0.098***	-0.275***	-0.440***	-0.378***	0.165***	0.103***
	(-14.60)	(-22.26)	(-21.17)	(6.48)	(9.07)	(-19.17)	(-24.23)	(-25.38)	(9.05)	(15.14)
Institutional funds	-0.286***	-0.385***	-0.335***	0.110***	0.049***	-0.286***	-0.389***	-0.337***	0.103***	0.051***
	(-14.82)	(-18.29)	(-17.08)	(7.48)	(8.27)	(-17.43)	(-20.23)	(-19.57)	(10.37)	(11.9)

Panel B: Cash flow-weighted portfolios

	Four factor model					Three-factor model				
	Alpha			Difference in Alphas		Alpha			Difference in Alphas	
	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive. vs. Negative	Positive vs. Average	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive vs. Negative	Positive vs. Average
All funds	-0.148***	-0.391***	-0.263***	0.242***	0.115***	-0.144***	-0.395***	-0.263***	0.251***	0.119***
	(-6.18)	(-19.52)	(-16.95)	(6.51)	(5.21)	(-7.95)	(-19.88)	(-20.11)	(9.40)	(7.07)
Retail funds	-0.118***	-0.396***	-0.259***	0.277***	0.141***	-0.110***	-0.400***	-0.258***	0.289***	0.148***
	(-4.636)	(-18.81)	(-17.06)	(6.5)	(5.24)	(-5.764)	(-19.15)	(-20.71)	(9.597)	(7.22)
Institutional funds	-0.217***	-0.372***	-0.282***	0.156***	0.065***	-0.217***	-0.380***	-0.286***	0.163***	0.069***
	(-11.92)	(-20.03)	(-17.39)	(11.35)	(13.75)	(-14.41)	(-19.63)	(-19.18)	(18.44)	(16.96)

Table 3.7

Fund Regression Approach: Mean Difference in Alphas between portfolios of different fund types

The table reports the statistical estimates for the differences between alphas of positive, negative, and average portfolios for different types of funds. Portfolio alphas are estimated using fund regression approach. Panel A reports the differences for alphas measured based on equally-weighted cash flow portfolio method. For instance, the first column from the left shows from the top to the bottom the difference in alphas of positive portfolios for retail versus all, institutional versus all, institutional versus retail funds respectively. Panel B reports corresponding differences for alphas measured based on cash flow-weighted portfolio method. The *t*-statistics in parentheses test whether the alpha difference between the portfolios is significantly different from zero. The *t*-statistics is based on the Newey-West covariance matrix. Differences are reported in percentage per month. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Panel A: Equally-weighted portfolios						Panel B: Cash flow-weighted portfolios					
	Four factor model			Three-factor model			Four factor model			Three-factor model		
	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio	Positive Cash Flow Portfolio	Negative Cash Flow Portfolio	Average Portfolio
Difference in Alphas Retail vs. All	0.002	-0.011***	-0.011***	0.003	-0.012***	-0.012***	0.030***	-0.005*	0.004***	0.034***	-0.004	0.005***
	(0.62)	(-13.14)	(-7.39)	(1.47)	(-10.15)	(-7.57)	(5.63)	(-1.76)	(7.06)	(5.92)	(-1.23)	(4.20)
Difference in Alphas Institutional vs. All	-0.005	0.041***	0.031***	-0.007	0.040***	0.030***	-0.068***	0.018*	-0.019***	-0.073***	0.015	-0.023***
	(-0.83)	(8.69)	(10.04)	(-1.44)	(7.46)	(9.04)	(-3.48)	(1.69)	(-10.21)	(-4.52)	(1.23)	(-6.96)
Difference in Alphas Institutional vs. Retail	-0.006	0.052***	0.043***	-0.010	0.051***	0.041***	-0.098***	0.023*	-0.023***	-0.107***	0.019	-0.028***
	(-0.77)	(9.44)	(9.58)	(-1.47)	(7.96)	(8.96)	(-4.02)	(1.71)	(-10.99)	(-5.32)	(1.23)	(-6.49)

Table 3.8

Fund Regression Approach: Mean Difference in (Alpha of Positive Portfolio - Alpha of Negative Portfolio), and in (Alpha of Positive Portfolio - Alpha of Average Portfolio) for different fund types

The table reports the statistical estimates for the differences between each two types of funds in alpha difference of positive versus negative, and positive versus average portfolios. Portfolio alphas are estimated using fund regression approach. Panel A reports the differences for alphas measured based on equally-weighted cash flow portfolio method. For instance, the first column from the left shows from the top to the bottom respectively the difference between retail versus all, institutional versus all, and institutional versus retail funds in alpha difference of positive versus negative portfolios. Panel B reports corresponding differences for alphas measured based on cash flow-weighted portfolio method. The *t*-statistics in parentheses test whether the difference is significantly different from zero. The *t*-statistics is based on the Newey-West covariance matrix. Differences are reported in percentage per month. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Panel A: Equally-weighted portfolios				Panel B: Cash flow-weighted portfolios			
	Four factor model		Three-factor model		Four factor model		Three-factor model	
	Positive vs. Negative	Positive vs. Average	Positive vs. Negative	Positive vs. Average	Positive vs. Negative	Positive vs. Average	Positive vs. Negative	Positive vs. Average
Difference in "VS" Alphas Retail vs. All	0.013***	0.013***	0. 014***	0.014***	0.035***	0.026***	0.038***	0.029***
	(7.64)	(13.01)	(8.08)	(9.87)	(8.92)	(7.02)	(8.26)	(6.81)
Difference in "VS" Alphas Institutional vs. All	-0.046***	-0.036***	-0.047***	-0.037***	-0.086***	-0.049***	-0.088***	-0.050***
	(-8.79)	(-13.07)	(-9.87)	(-14.86)	(-5.96)	(-4.45)	(-6.37)	(-5.43)
Difference in "VS" Alphas Institutional vs. Retail	-0.059***	-0.049***	-0.061***	-0.052***	-0.121***	-0.075***	-0.126***	-0.079***
	(-8.62)	(-13.51)	(-9.94)	(-14.32)	(-6.78)	(-5.28)	(-7.33)	(-6.45)

Table 3.9
Smart money effect: Small versus Large Funds

For each sample, each month from January 1999 to May 2009, mutual funds are grouped into either the positive cash flow portfolio or the negative cash flow portfolio based on the sign of the net cash flow experienced by each fund during the previous month. Portfolio performance is evaluated based on the estimated portfolio alpha. The four-factor portfolio alpha is calculated as the intercept from the monthly time series regression of portfolio excess returns on the market excess return (MKTRF) and mimicking portfolios for size (SMB), book-to-market (HML), and momentum (UMD) factors (MKTRF, SMB, HML, UMD are obtained from CRSP): $r_{p,t} = \alpha_p + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + e_{pt}$. The three-factor alpha is based on a model that excludes the momentum factor. The table reports the difference in alphas between (a) the positive cash flow portfolio and the negative cash flow portfolio, and (b) the positive cash flow and the average portfolio. EW means that reported value calculated for equally-weighted cash flow portfolios, CW means that a value relates to cash flow-weighted portfolios. Panel A reports results for the smallest funds defined as funds with TNA of the lowest 25 percentile. Panel B reports results for the largest funds defined as funds with TNA of the highest 25 percentile. Differences in alphas are reported as percent per month. The *t*-statistics based on the Newey-West covariance matrix are reported in parenthesis. Statistical significance is denoted only for alphas. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Panel A			Panel B		
	Smallest 25 percentile			Largest 25 percentile		
	All Funds	Retail Funds	Institutional Funds	All Funds	Retail Funds	Institutional Funds
Four-Factor Model						
Positive vs. Negative (EW)	0.030	0.020	0.082*	0.066	0.073	0.061
	(0.74)	(0.50)	(1.76)	(1.14)	(1.13)	(1.56)
Positive vs. Negative (CW)	0.243***	0.306***	0.144	0.081	0.090	0.077
	(2.83)	(3.17)	(1.50)	(0.91)	(0.94)	(1.12)
Three-Factor Model						
Positive vs. Negative (EW)	0.039	0.031	0.088*	0.086	0.095	0.074
	(0.97)	(0.72)	(1.86)	(1.13)	(1.14)	(1.38)
Positive vs. Negative (CW)	0.261***	0.328***	0.154	0.114	0.127	0.095
	(2.87)	(3.30)	(1.53)	(0.94)	(0.94)	(1.17)
Number of Fund-Months	195,584	130,263	65,321	194,614	140,533	54,081

Table 3.10
Smart money effect: Expansion versus Recession Periods

For each sample, each month from January 1999 to May 2009, mutual funds are grouped into either the positive cash flow portfolio or the negative cash flow portfolio based on the sign of the net cash flow experienced by each fund during the previous month. Portfolio performance is evaluated based on the estimated portfolio alpha. The four-factor portfolio alpha is calculated as the intercept from the monthly time series regression of portfolio excess returns on the market excess return (MKTRF) and mimicking portfolios for size (SMB), book-to-market (HML), and momentum (UMD) factors (MKTRF, SMB, HML, UMD are obtained from CRSP): $r_{p,t} = \alpha_p + \beta_{1,p} MKTRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + e_{pt}$. The three-factor alpha is based on a model that excludes the momentum factor. The table reports the difference in alphas between (a) the positive cash flow portfolio and the negative cash flow portfolio, and (b) the positive cash flow and the average portfolio. EW means that reported value calculated for equally-weighted cash flow portfolios, CW means that a value relates to cash flow-weighted portfolios. Panel A reports results for expansion months. Panel B reports results for recession months. Differences in alphas are reported as percent per month. The *t*-statistics based on the Newey-West covariance matrix are reported in parenthesis. Statistical significance is denoted only for alphas. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level. Level of statistical significance for difference between corresponding coefficients for expansion and recession months is reported only for the coefficients for which the difference is significant on at most 10% level. In those cases, statistical significance on at least 10% level is denoted by (a).

	Panel A			Panel B		
	Expansion			Recession		
	All Funds	Retail Funds	Institutional Funds	All Funds	Retail Funds	Institutional Funds
Four-Factor Model						
Positive vs. Negative (EW)	0.074*	0.073*	0.076*	0.091	0.098	0.044
	(1.71)	(1.69)	(1.75)	(1.23)	(1.14)	(0.86)
Positive vs. Negative (CW)	0.134	0.132	0.160**	0.118	0.115	0.039
	(1.22)	(1.09)	(2.19)	(1.24)	(1.46)	(0.55)
Three-Factor Model						
Positive vs. Negative (EW)	0.125*	0.128*	0.114**(a)	0.022	0.015	0. 004(C)
	(1.89)	(1.81)	(2.16)	(0.39)	(0.23)	(0.07)
Positive vs. Negative (CW)	0.225*	0.234*	0.213***(a)	-0.081	-0.104	-0.090(C)
	(1.98)	(1.85)	(2.89)	(-0.68)	(-0.65)	(-0.83)
Number of Fund-Months	600,253	434,205	166,048	178,536	118,563	59,973

Table 3.11
Determinants of Net Cash Flows: Retail versus Institutional Funds

The table reports the coefficients from pooled time-series cross-sectional OLS regressions of funds' monthly net cash flow on the momentum (UMD) loading calculated over the previous 36 month of fund return, fund total net assets estimated to the end of the previous month, the 1st lag of fund's annual return, fund risk estimated as the standard deviation of fund return over the previous 12 months, the monthly normalized cash flow of fund's IOC, turnover ratios defined as a minimum of aggregate purchases or sales of securities during the year, divided by average fund total net assets, fund expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. We also include time-style interaction dummies for each combination of month and style. Panel A (Specification (1)) reports the results for all funds in the sample. Panel B (Specification (2)) reports the results of the regression in which we interact each of the explanatory variables once with a dummy identifying retail funds and once more time with the dummy identifying institutional funds. We also include the dummy identifying institutional funds as a separate variable. The columns titled "Difference Institutional vs. Retail" reports differences between the coefficients of institutional and retail funds from the regression analysis summarized in Specification (2), exhibiting the difference in effect of respective variable on fund money flows of the two types of funds. The t-statistics are reported in parentheses. The standard errors are clustered by funds. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Panel A	Panel B		
	(1)	(2)		
	All Funds	Retail Funds	Intuitional Funds	Difference Institutional vs. Retail
Intercept/ Institutional Dummy	5.111***	3.090**	3.044*	3.044*
	(4.28)	(2.24)	(1.99)	(1.99)
UMD Loading	4.238***	3.962***	6.601***	2.639*
	(4.49)	(3.59)	(5.22)	(1.72)
Fund's Total Net Assets	0.0002	0.0001	0.0074***	0.0074***
	(0.56)	(-0.24)	(5.78)	(5.59)
Lagged Annual Return	0.315***	0.329***	0.257***	-0.072***
	(18.25)	(17.83)	(15.17)	(-5.90)
Fund Risk	0.083***	0.118***	-0.054	-0.172***
	(2.30)	(2.96)	(-1.35)	(-4.07)
IOC Net Cash Flow	0.001***	0.002***	0.001***	-0.001***
	(8.59)	(8.83)	(4.68)	(-4.76)
Turnover Ratio	-0.012***	-0.008***	-0.009***	-0.001
	(-4.95)	(-2.83)	(-2.76)	(-0.15)
Expense Ratio	-1.756***	-1.250***	-0.200	1.050
	(-6.33)	(-3.09)	(-0.33)	(1.44)
Fund Age	-0.025***	-0.021***	-0.053***	-0.032***
	(-6.57)	(-5.26)	(-5.69)	(-3.20)
R sq. adjusted	0.030	0.049		
No. Fund-Months/Entities	7,995	7,995		
No. Fund- Entities	393,360	393,360		

Figure 3.1

Number of Mutual Funds over the period between January 1999 and May 2009

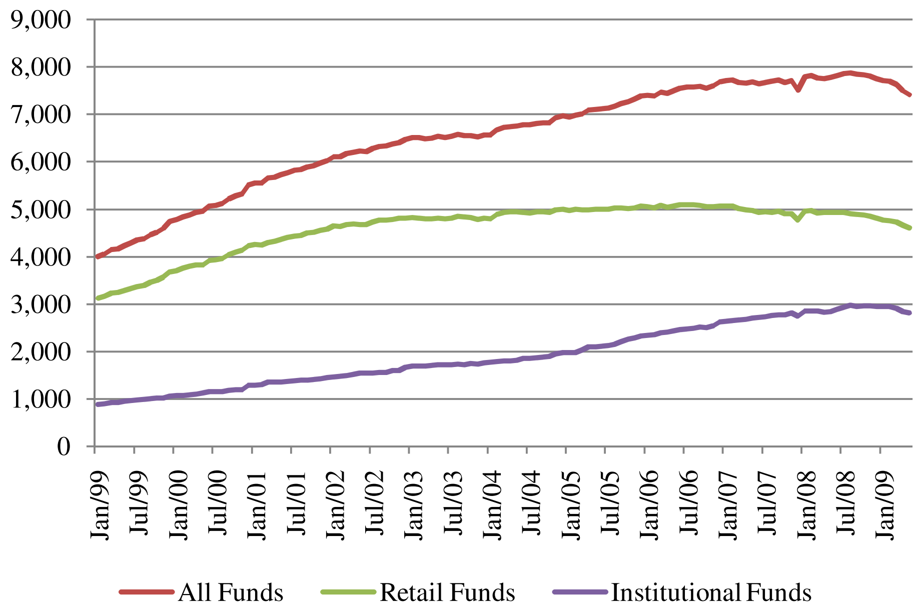


Figure 3.2

Cumulative Monthly Total Net Asset Value (in millions of U.S. dollar) of corresponding group of Mutual Funds over the period between January 1999 and May 2009

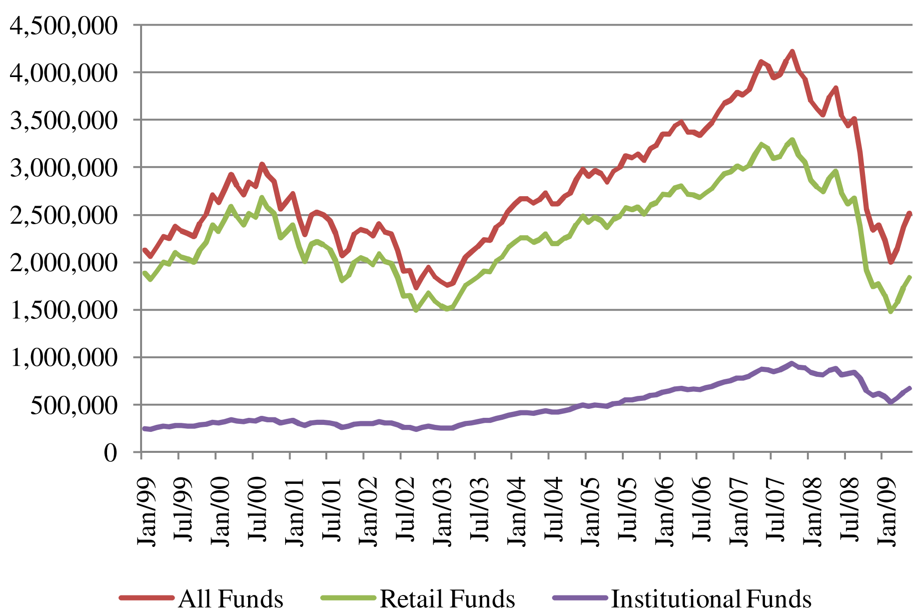
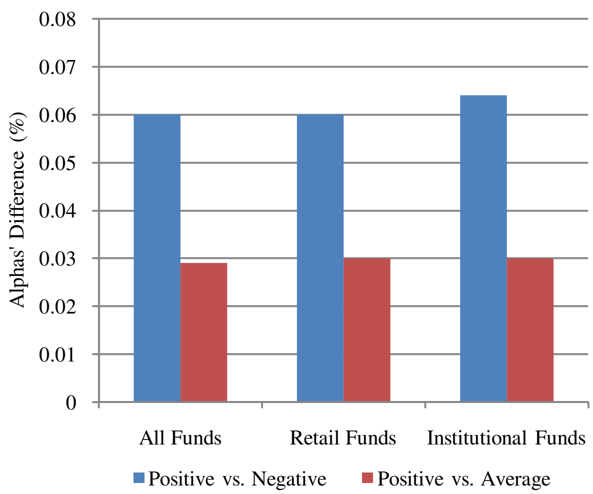


Figure 3.3

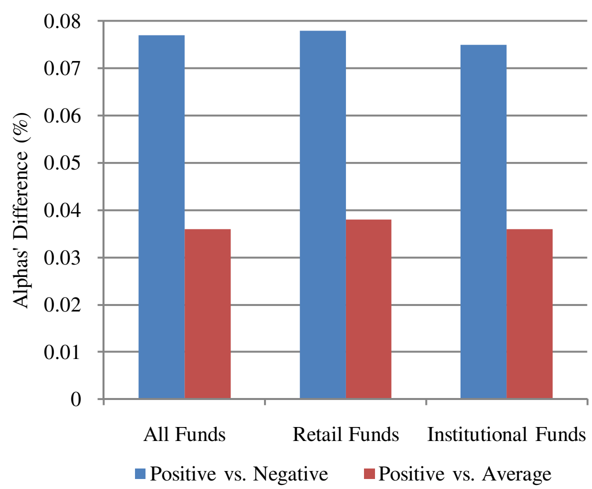
Alphas' Differences: for Positive vs. Negative, and Positive vs. Average Portfolios

The figure summarizes the differences in alphas between the positive cash flow portfolio and the negative cash flow portfolio, and the positive cash flow portfolio and the average portfolio estimated based on the portfolio regression approach and reported in Table 3.3. Graph A shows the differences measured based on four-factor model for equally-weighted portfolios. Graph B shows the differences measured based on three-factor model for equally-weighted portfolios. Graph C shows the differences measured based on four-factor model for cash flow-weighted portfolios, and graph D shows the differences measured based on three-factor model for cash flow-weighted portfolios.

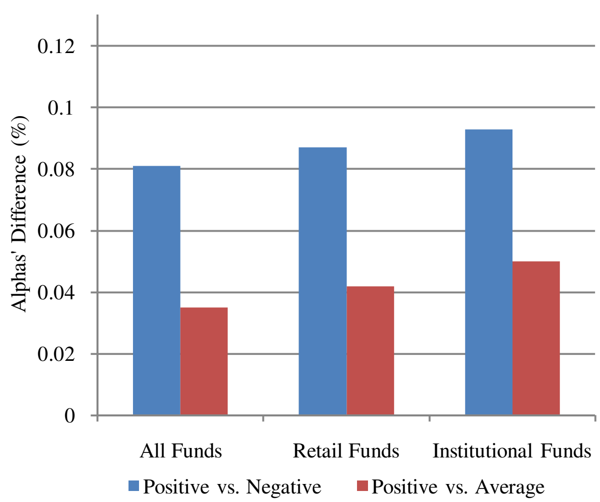
A. For the four-factor model (equally-weighted portfolios)



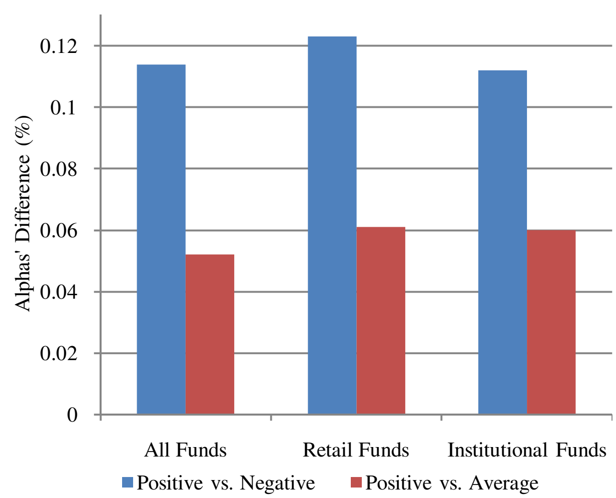
B. For the three-factor model (equally-weighted portfolios)



C. For the four-factor model (cash flow-weighted portfolios)



D. For the three-factor model (cash flow-weighted portfolios)



Appendix 3.1

Recession*– Expansion periods over the sample period February 1999 – May 1999 (based on NBER business cycle classification)**

Business Cycle Reference Dates		Duration in Months	
Beginning Date	End Date	Recession	Expansion
February 1999	February 2001		25
March 2001	October 2001	8	
November 2001	November 2007		73
December 2007	May 2009	18	
Total		26	98

*"A recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales." (NBER)

**Source: an official website of the National Bureau of Economic Research (NBER), http://www.nber.org/cycles.html; visited on 07.02.2010.

CHAPTER 4

The Determinants of the Investment Flows: Retail versus Institutional Mutual Funds

In this chapter we compare fund selection criteria for retail and institutional mutual funds' investors. We find that clients of institutional mutual funds use more quantitatively sophisticated criteria, such as risk-adjusted return measures and tracking error, than investors of retail mutual funds do. In line with momentum trading literature, we show that institutional investors demonstrate stronger momentum driven behavior. Additionally, our results indicate that relative performance of a fund with respect to a benchmark is an important criterion in fund selection process for investors of both types of funds. We also provide evidence that the convex form of flow-performance relationship, documented by existing literature, is driven mostly by retail funds. Finally, we find that flow patterns of both fund types vary across the business cycle. Moreover, the differences between the two patterns also change across the business cycle.

4.1 Introduction

Over the past decades, the mutual fund industry has grown considerably. Moreover, since the early 1990s, a new class of so-called institutional funds has emerged. In contrast to retail funds that focus on regular individuals, institutional funds primarily target institutional investors such as corporations, non-profit organizations, endowments, foundations, municipalities, pension funds, and other large investors, including wealthy individuals. As a result, the typical retail fund investor differs noticeably from the typical institutional fund investor in his level of financial sophistication, investment objectives, and search costs.[31] Consequently, criteria that these two types of investors base their investment decision on are likely to vary, making investment flow patterns of retail and institutional funds differ too.

There is a lot of mutual fund research that addresses investment flows. Edelen (1999) shows that investment flows to a large extent determine fund manager trading activity causing fund managers to engage in liquidity motivated trading that they otherwise would have avoided. In addition, mutual fund research documents that investment flows affect fund manager incentives with respect to risk. Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue that fund manager compensation tied to amount of assets under management together with the convex form of the fund flow-performance relationship, creates incentives for

[31] See, for example, Alexander, Jones and Nigro (1998), Del Guercio and Tkac (2002), and Palmiter and Taha (2008).

managers to shift fund risk. Johnson (2005) emphasizes the importance of flow examination due to the potential influence of flows on fund performance.

Researchers investigating the determinants of mutual fund flows established the importance of past performance.[32] Some of the literature shows the effect of flows on fund managers' behavior.[33] Other studies shed light on the relationship between search costs and fund flows, and the influence of fund marketing and advertisement on flows.[34]

However, those studies do not usually distinguish between flows of funds targeting different types of investors. Meanwhile, the growing proportion of institutional funds – both in term of the number of funds and assets under management – makes the recognition and understanding of those differences especially important.

In this chapter, we study determinants of mutual funds' investment flows separately for retail and institutional funds, examining how fund selection criteria vary across investors of these two types of funds. Examination of flows at the monthly frequency allows us to get a more precise picture of fund flows' dynamic as compared to analysis based on quarterly or annually estimated flows.[35]

We conduct our investigation using complete universe of diversified U.S. equity mutual funds for the period January 1999 to May 2009 in the CRSP Survivor-Bias Free U.S. Mutual Fund Database. We categorize funds into retail and institutional based on the corresponding designation provided by CRSP. Note that this classification may not be a precise identifier of investor type. For instance, the final investment decision of 401k plans' participants is taken by an individual investor, while their capital flows may combine flows of either an institutional or a retail fund. Nevertheless, it seems reasonable to assume that the classification of funds into retail and institutional implies differences in investor composition of the two types of fund. In particular, the overwhelming majority of retail fund investors apparently are regular individuals. At the same time, institutional investors, if participating in mutual funds, can be expected to

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[32] See, for example, Chevalier and Ellison (1997), Gruber (1996), Patel, Zeckhauser, and Hendricks (1994), Ippolito (1992), Sirri and Tufano (1998), Ivkovich and Weisbenner (2009), and Ferreira, Keswani, Miguel, and Ramos (2009).
[33] See, for example, Brown, Harlow, and Starks (1996), and Chevalier and Ellison (1995).
[34] See, for example, Sirri and Tufano (1998), and Barber, Odean and Zheng (2005).
[35] Barber, Odean and Zheng (2005) investigate mutual fund flows estimated at quarterly frequency; Berk and Tonks (2009), Del Guercio and Tkac (2002), and Sirri and Tufano (1998) study mutual fund flows measured at annual frequency.

invest in institutional funds. Furthermore, presumably more sophisticated institutional investors influence flows of institutional funds, while flows of retail funds are determined by investment decisions of unsophisticated – individual investors.

In a related study, Del Guercio and Tkac (2002) compare flow patterns across investor types. Our study differs from and complements their study in a number of ways. Firstly, their conclusions are based on the comparison of investment flows of pension fund sponsors and retail mutual fund investors. However, investor composition of institutional mutual funds comprises a broad variety of investors, among which pension fund sponsors represent only one particular type.[36] Therefore, while investment pattern of pension fund sponsors may be expected to resemble that of institutional fund investors, Del Guercio and Tkac's (2002) result does not provide an empirical answer on whether or not this is the case. Implementation of a mutual fund type identifier allows us to conduct more general and precise comparison of differences in fund selection criteria of retail versus institutional mutual fund investors. Secondly, Del Guercio and Tkac (2002) base their analysis of retail mutual funds on a relatively small sample comprising less than 500 equity retail mutual funds and covering the period between 1987 and 1994, while we use the complete universe of U.S. domestic equity mutual funds currently actual during the most recent period – between years 1999 and 2009. Our final sample includes almost 7,800 retail funds and more than 3,900 institutional funds. Thirdly, Del Guercio and Tkac (2002) investigate investment flows estimated at the annual horizon, thereby ignoring shorter-term flow dynamics. We examine mutual fund flows calculated at the monthly frequency, which allows us to get a more precise picture of fund flow character as compared to an analysis based on quarterly or annual flows.[37] Furthermore, we expand on the set of factors determining flows of each type of fund, investigating effects of factors such as fund expense ratio and momentum exposure. Finally, to account for possible variation in investment flow pattern across the business cycle, we examine the pattern separately for NBER expansion and recession periods.[38] This examination is

[36] According to Cohen (2003), factors determining asset allocation decisions of institutions might vary for different types of institutions

[37] Barber, Odean and Zheng (2005) investigate mutual fund flows estimated at the quarterly frequency; Berk and Tonks (2009), Del Guercio and Tkac (2002), and Sirri and Tufano (1998) study mutual fund flows measured at annual frequency.

[38] We adopt NBER dates of expansion and recession months to define the business cycle following existing literature investigating flows and performance of mutual funds across the business cycle (see for examples Moskowitz (2000), Kosowski (2006), and Cederburg (2008)).

especially valuable in the light of findings of prior literature documenting that mutual fund flows are not time invariant and tend to change with market conditions.[39]

Consistent with the investor profile, we find a number of differences in investment flow patterns between retail and institutional funds. First, we find that customers of institutional mutual funds react more to criteria considered sophisticated. For example, while investment flows of both types of funds are significantly and positively related to a variety of risk-adjusted performance measures, flows of institutional funds are significantly stronger related to those measures. We also find that the observed difference in flow-performance relationship increases during recession periods.[40] On the other hand, flows of retail funds are more sensitive to unadjusted performance measures.

In line with the empirical findings of previous literature, the flow-performance relationship appears to have a non-linear form.[41] However, the form of this relationship is not the same for flows of retail and institutional funds. For retail funds, the relationship appears to have a convex form, implying that investors of those funds tend to allocate disproportionally more into good performers, while they do not punish bad performers by withdrawing money. For institutional funds, however, the form of the flow-performance relationship appears to be merely linear in the part reflecting the flow-performance relationship for well performing funds. Conversely, for some of performance measures, the form is concave in the part reflecting punishment of bad performers. This result implies that investors of institutional funds withdraw assets from poor performing funds punishing the worst performers the hardest, while allocating assets into well performing funds.

Our findings on differences in the form of the flow-performance for retail and institutional funds relationship contribute to the extensive literature on incentives and driver factors of fund manager behavior. The convex shape of the flow-performance relationship,

[39] Edelen and Warner (2001) and Boyer and Zheng (2008) show that market conditions affect mutual fund flows, documenting a positive relationship between flows into U.S. equity mutual funds and market returns. Birnbaum, Kallberg, Koutsoftas and Schwartz (2004) document reluctance of both retail and institutional investors to withdraw their funds in bearish market conditions. Cederburg (2008) finds that investors demonstrate strong return chasing behavior during expansions, while they do not chase returns during recessions.

[40] Findings of prior literature reveal that, at risk-adjusted basis, mutual funds perform better during recession periods than during expansions (see for examples Moskowitz (2000), Kosowski (2006), Avramov and Wermers (2006), and Cederburg (2008)). Those results may explain why, in our nalysis, risk-adjusted performance measures appear to have a stronger influence on fund flows during recession months, and why this tendency is found to be especially pronounced among – presumably more sophisticated – institutional investors.

[41] See, for example, Ippolito (1992), and Sirri and Tufano (1998).

observed for the funds of retail fund sample, implies that "winners take all". As a result, fund managers, who are typically compensated as a percentage of assets under management, have an implicit incentive to raise the risk of their portfolios in order to increase the chances to be among the winners, without taking a risk of being punished in case of failure.[42] At the same time, our results show that concave-convex form of the flow-performance relationship for institutional funds weakens fund manager incentive to follow the mentioned risk-shifting behavior.

In addition, our results indicate that relative performance of funds with respect to benchmarks is an important criterion in the fund selection process. Both institutional and retail funds outperforming their investment objective category (IOC) experience higher flows than underperforming funds.[43] Similarly, funds outperforming the market are rewarded with higher inflows. Benchmarks appear to have a stronger influence among investors of retail funds. In line with Guercio and Tkac's (2002) findings, the influence of the magnitude of the excess returns on fund flows is found to be especially pronounced at the top of the performance distribution.

We find a significant negative relationship between investment flows and tracking error – a measure of diversifiable risk – for both institutional and retail mutual funds. This is in contrast to the results of Del Guercio and Tkac (2002), documenting no evidence for influence of fund tracking error on mutual fund flows. Our results indicate that both institutional and retail fund investors tend to punish funds with a higher tracking error through withdrawing assets from those funds. At the same time, in line with the logic of the reference paper, this relationship appears to be much more pronounced for flows of institutional funds, whose clients presumably represent more sophisticated investors. Furthermore, for institutional funds, the influence of the tracking error on investment flows is stronger during expansion periods. Flows of retail funds are, though weaker than institutional flows, negatively related to tracking error during bullish periods and positively related to tracking error during bearish periods.

Based on research that documents evidence for momentum following behavior, we examine how momentum exposure of each type of fund affects fund flows, and whether this effect differs across fund types.[44] We find evidence suggesting that flows of both types of funds are significantly positively related to fund momentum exposure. However, the results suggest

[42] See, for example, Brown, Harlow, and Starks (1996), and Chevalier and Ellison (1997).
[43] From here and further in this paper we use IOC abbreviation to denote "investment objective category" term.
[44] See, for example, Nofsinger and Sias (1999), Jegadeesh and Titman (1993), Grinblatt and Keloharju (2001), Froot and Teo (2004), Sias (2004), and Gallo, Phengpis, and Swanson (2008).

that attractiveness of momentum following funds diminishes during recession months. Moreover, the effect of business cycle on flow-momentum relationship is not the same for institutional and retail funds. While momentum-trading institutional funds attract considerably higher inflows than their retail counterparts during expansions, those funds experience relatively lower flows over recessions. This finding is consistent with the literature documenting variation of investor behavior across different market conditions.[45]

In addition, consistent with the previous studies, we find that both institutional and retail funds with higher inflows in the past continue to experience higher inflows in the subsequent periods.[46] Moreover, this effect appears to be stronger for institutional funds. This result suggests that institutional fund investors exhibit stronger herding behavior, which is in line with the results reported by prior literature.[47]

Finally, fund expense ratio also appears to have a significant influence on flows of both types of funds. In particular, mutual funds with lower expense ratio experience higher inflows. Retail fund investors demonstrate stronger sensitivity to fund expense ratio, and the difference is even larger during recession periods. Experiencing wealth depreciation, individual investors, presumably, are even more sensitive to costs associated with their participation in mutual funds during recession periods than during expansions. At the same time, investors of institutional funds – probably due to the fact that they do not invest their own money – are less sensitive to the price of services and ready to pay for higher quality or more convenient service.

The remainder of this chapter is organized as follows. Section 4.2 provides an overview for institutional and retail mutual funds. Section 4.3 discusses characteristics of individual and institutional investors and potential reflection of those characteristics in flow determinants. Section 4.4 describes the mutual fund data sample. Section 4.5 explains the methodology and reports results of the analysis. Section 4.6 concludes.

4.2 Industry Overview: Retail versus Institutional Funds

[45] See, for example, Grinblatt and Keloharju (2001), Cederburg (2008), Shrider (2009), Birnbaum, Kallberg and Schwartz (2004), and Glode, Hollified, Kacperczyk, and Kogan (2009).
[46] See, for example, Hendricks, Patel, and Zeckhauser (1993), and Del Guercio and Tkac (2002).
[47] See, for example, Nofsinger and Sias (1999), and Lakonishok, Shleifer and Vishny (1992b).

Funds focused on institutional investors represent a relatively recent trend starting in the early 1990s (James and Karceski (2006)). The formation of institutional funds resulted in a division of mutual funds into individual and institutional oriented. Thus, funds serving individual clienteles are known as “retail” funds, while funds targeting institutional investors – “institutional”. There is no formal definition of retail or institutional fund. The main criteria that are usually considered to classify funds into retail and institutional are minimum investment requirement declared by fund and the distribution channel of fund shares. Morningstar, for example, classifies as institutional funds with minimum initial investment requirements of at least $100,000 (James and Karceski (2006)). In this study, we use fund classification provided by CRSP, which adopts Lipper fund type categorization. To be classified as institutional by Lipper, a fund has to have a minimum investment requirement of at least $100,000 and fund’s shares have to be distributed to or through an institution.[48] In addition, funds that designate themselves as institutional are usually recognized as those.[49]

The size of the institutional segment of the mutual fund market has grown dramatically in recent years, both in terms of the number of funds and assets under management. For example, James and Karceski (2006) report that at the beginning of their sample period – 1986 – the number of open-end bond and equity institutional funds was 22, while at the end of the sample period – the end of year 1998 – there were 873 funds. Thus, the number of institutional funds grew at 40-folds during the sample period. In contrast, the number of retail funds increased from 786 to 5,076 (increase of around 650%) during the same period. At the same time, the amount of assets managed by institutional funds grew from 3.2 billion at the beginning of the sample period – year 1986 – to over $302 billion by the end of the sample period – year 1998[50].

Our sample also depicts considerable growth of proportion of institutional funds. Thus, at the beginning of our sample period – January 1999 - institutional funds represented around 20% of all funds managing merely 12% of assets, while at the end of the period – May 2009 – almost 40% of all funds were institutional funds accounting for 22% of assets under management.[51]

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[48] We received this information during phone conversation with one of the Lipper officers responsible for this field.

[49] Both Morningstar and Lipper consider a fund as institutional if it designate it as such (for Morningstar we get this information based on the study of James and Karceski (2006), and for Lipper based on our e-mail dialog with one of the Lipper officers responsible for this field.

[50] In their study, James and Karceski (2006) categorize fund as an institutional if the fund is designated as such by Morningstar.

[51] In our sample over the period between January 1999 and May 2009, the number of institutional funds grew at faster pace than the number of retail funds, with the number of institutional funds increasing 322 percent (from 884

Figures 4.1 and 4.2 show the evolution of both groups of funds in our sample over the period between January 1999 and May 2009.

[Please insert Figures 4.1 and 4.2 about here]

Numbers reported by Investment Company Institute confirm the observed tendency. ICI estimates that institutions held more than 1.7 trillion dollars in equity, bond, money market and hybrid open-end mutual funds at year-end 2008 (out of a total of $9.6 trillion in these funds). That is compared with 0.7 trillion dollar held by institutional investors in mutual funds at year-end 2000, which represented merely 10% of total assets of the mutual fund industry in year 2000 (7 trillion dollar).[52]

Although the same companies that have a part in running retail mutual funds (banks, insurance companies, brokers, and fund advisory companies) operate institutional mutual funds, these funds have several distinguishing characteristics. Besides considerably higher minimum initial investments, institutional funds usually offer lower costs to investors compared to retail funds. So, only a insignificant minority of institutional funds have front or deferred loads, redemption fees or 12b-1 marketing expenses.

Some of the institutional funds in our sample have retail counterparts. Since the Investment Company Act requires different classes of shares of the same fund to have the same return before distribution expenses, the institutional and retail shares of such funds, while holding the same portfolio, are claims on separate asset pools or trusts. This structure is imposed by the differences in services that each type of fund requires from the fund manager.[53] For instance, management fees may be lower for the institutional investor shares than for the retail, since an institutional sponsor may provide bookkeeping services and transact with the fund through an omnibus account. The institutional and the retail peers file separate prospectuses.

Only a small number of academic studies investigate retail versus institutional funds, mainly concentrating on performance characteristics. James and Karceski (2006) find that, despite significantly lower management expenses, the average return on institutional funds is no better than the average return on retail funds. Even on a risk-adjusted basis, institutional funds

to 2844 funds), and the number of retail funds increasing 53 percent (from 3042 to 4656 funds). Assets under management hold by institutional funds increased almost three-fold (from 247 billion to 671 billion), while assets under management of retail funds remained nearly the same (1883 billion to 1840 billion).

[52] See, ICI "Fact Book 2009". ICI defines a mutual fund shareholder as institutional if the shareholder represents an institution such as a business, financial, or non-profit organization.

[53] See James and Karceski (2006).

performance is similar to retail funds. In addition, the authors report that institutional funds with low initial investment requirements and funds with retail peers perform worse than other institutional funds both before and after adjusting for risk and expenses. Finally, examining the relationship between fund cash flows and performance, the authors find that cash flows into institutional funds with high minimum investment requirements are significantly more sensitive to risk-adjusted measures of performance than are flows into small institutional funds or retail funds.

Investigating the relationship between the performance and characteristics of domestic, actively managed institutional equity mutual funds, Baker, Haslem and Smith (2009) show that large funds tend to perform better, which suggests the presence of significant economies of scale. The authors also document evidence on the positive relationship between cash holdings and performance.

Our study contributes to existing literature revealing determinants of mutual funds' investment flows separately for retail and institutional funds, examining how fund selection criteria vary across investors of these two types of funds.

So far, we discussed specific characteristics of retail and institutional funds. As noted above, target clientele is one of the main differences between those two types of funds. Thus, the individual investor is a typical client of retail funds, while institutional investors are usually clients of institutional funds. In the next section, we discuss characteristics of individual and institutional investors and their potential reflection on fund selection process.

4.3 Investor Characteristics and Flow Determinants

Academic research on investor behavior often distinguishes between individual and institutional investors, referring to regular households as individual investors and organizations or groups of individuals, investing through intermediaries, as institutional investors. Such a division reflects fundamental differences between those two types of investors in characteristics determining investor behavior. First, individual investors are considered to be unsophisticated in financial issues.

As documented by Capon, Fitzsimons and Prince (1996), who conduct a survey on mutual fund purchases by U.S. households, most individual mutual fund investors are naïve, affected by many non-performing factors when taking their investment decisions, and have little knowledge in financial issues in general and in their mutual fund investments in particular. Based on the results of a survey of U.S. mutual fund individual investors, Alexander, Jones and Nigro (1998) come to a similar conclusion reporting insufficiently low level of financial literacy of individual investors. Summarizing the findings of academic literature that studies mutual fund individual investor's profile, Palmiter and Taha (2008) conclude that individual investors are mostly ignorant and financially unsophisticated: the majority are unaware of the basic characteristics of the funds they invest in, do not take into account the risk and the costs associated with their investments in the funds, and chase past returns.

In contrast, institutional investors are commonly considered more sophisticated. Del Guercio and Tkac (2002) characterize pension fund sponsors – the typical institutional investor – as more sophisticated in financial issues than retail mutual funds' investors. The authors note that pension fund sponsors are often professionals specializing in investment management. Moreover, Del Guercio and Tkac (2002) find that pension fund sponsors rely more on quantitatively sophisticated fund performance evaluation methods, such as fund Jensen's alpha, fund relative performance with respect to a benchmark, and fund tracking error.[54]

However, institutional investor has no need to be a financial expert in order to take an advantage on individual investor in the quality of their investment decision. The economies of scale provide institutional investors with better access to services of professional experts. Moreover, the economies of scale make search costs for institutional investors considerably lower compared to those for individuals.[55] Furthermore, a large amount of assets held by institutional investors provides them with much wider diversification opportunities. Simultaneously, there is another essential difference between individual and institutional investors. In contrast to institutional investors, individuals invest on their own behalf.[56]

Given that the typical institutional investor is more sophisticated in financial issues than the typical individual investor, institutional investors can be expected to base their investment

[54] Del Guercio and Tkac (2002) note that pension fund sponsors usually rely on consultant recommendations when selecting and evaluating money managers. At the same time, consultants' screening includes extensive quantitative analysis based on such risk-adjusted measures as Jensen's alpha and tracking error. Moreover, according to the authors, those measures are commonly included in pension fund databases and evaluation software packages. In addition, pointing out an importance of a benchmark, the authors mention that pension fund sponsors usually select and evaluate fund managers with respect to investment style.

[55] See, for example, Sirri and Tufano (1998).

[56] See, for example, Lakonishok, Shleifer and Vishny (1992), Del Guercio and Tkac (2002).

decisions on more sophisticated selection criteria than individual investors do. In fact, comparing selection criteria of retail mutual fund investors with pension funds, Del Guercio and Tkac (2002) document that pension funds - representing more sophisticated investors - use more such quantitatively sophisticated measures as tracking error and Jensen's alpha. In contrast, the authors find that retail mutual fund investors pay greater attention to raw returns. Yet, they note that flows of retail mutual funds are also positively correlated with some of more sophisticated performance measures such as Jensen's alpha. The authors explain this result by high correlation between Jensen alpha and broadly accessible fund evaluation measures such as the Morningstar ranking. In their more recent study, Del Guercio and Tkac (2008) reveal that Morningstar rankings indeed positively affect investment flows into retail mutual funds. Summarizing the academic literature that examines the profiles of mutual fund investors, Palmiter and Taha (2008) come to a similar conclusion, reporting that individual mutual fund investors tend to chase past returns.

Nevertheless, institutional investors may exhibit return chasing behavior as well. For instance, Lakonishok, Shleifer and Vishny (1992) conjecture that investment decisions by some institutional investors are affected by agency conflicts. Thus, an institution may entrust with money management outside managers in attempt to avoid responsibility in the case of poor performance, making thereby the fund selection process mainly based on past returns.

Extensive research investigates whether information on historical return can be helpful in prediction future returns.[57] Though the answer to this question is still the subject of controversy, this literature suggests that return persistence is mostly observable among the best and worst performing funds. [58] Accordingly, the worst performing funds continue to perform poorly, while the best performers continue generating high returns. Sharp (1966) finds persistence for both low and high-ranked mutual funds. Hendricks, Patel and Zeckhauser (1993) introduce the concept of "hot hands" meaning the tendency of the best performing funds to continue to outperform in the subsequent periods. Grinblatt and Titman (1992), and Goetzmann and Ibbotson (1994) also provide evidence of return persistence among the best performing funds. Simultaneously,

[57] See, for example, Sharp (1966), Grinblatt and Titman (1989, 1992), Brown, Goetzmann, Ibbotson and Ross (1992), Hendricks, Patel and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Elton, Gruber and Blake (1996), Carhart (1997), Bollen and Busse (2002), Wermers (2003), Kosowski, Timmermann, Wermers and White (2006), and Fama and French (2008).
[58] See, for example, Hendricks, Patel, and Zeckhauser (1993), Carhart (1997), Grinblatt and Titman (1992), and Goetzmann and Ibbotson (1994).

Ibbotson and Goetzmann (1994) document return persistence among the worst performing funds. In their recent study, Berk and Tonks (2007) come to the similar conclusion. Fama and French (2008) find, though temporary, persistence in fund three-factor alpha among both winners and losers. Thus, the authors report that funds that underperformed in the previous year also continued to perform poorly in succeeding years. According to the authors, the observed persistence is a result of investors' reluctance to withdraw assets from poorly performing funds.

Comparing the flow-performance relationship of pension fund managers and retail mutual funds, Del Guercio and Tkac (2002) find that pension investors punish poorly performing funds by withdrawing assets from those funds. In contrast, mutual fund investors do not react to bad performance of losers by withdrawing assets, while allocate disproportionally more in the recent winners. In fact, earlier study by Sirri and Tufano (1998) reports that individual mutual fund investors allocate asymmetrically more assets in funds with high performance in the previous period. Ivkovich and Weisbenner (2009) document that individual mutual fund investors tend to sell recently losing funds, while reluctant to sell the recent winners. At the same time, Chevalier and Ellison (1997) argue that the flow-performance relationship creates incentives for mutual fund managers to increase or decrease the riskiness of the fund that are dependent on the fund's year-to-date return, reporting that mutual fund managers tend to change portfolio risk at the year end. Ferreira, Keswani, Miguel and Ramos (2009) study variation in the flow-performance relationship across countries. They find that the relationship tends to be less convex in countries with a higher level of economy and a more developed mutual fund industry, explaining their findings by the higher level of financial sophistication of investors, and lower costs of participation in mutual funds attributing developed countries.[59] In addition, the authors show that the level of portfolio risk is higher in countries with more convex form of the flow-performance relationship.[60]

Therefore, if investors would consider those findings when selecting funds, they could be expected to allocate more assets into the recent winners, expecting them to repeat high return, while withdrawing assets from the worst-performing funds, realizing high probability that those funds will continue to underperform. If that was the case, the flow-performance relationship

[59] The authors use the following variables to identify economic development of a country and the level of mutual fund industry development: (for economic development) GDP, the average number of years in school, and the proportion of population using the internet; (for mutual fund industry) the age and size of the industry, and the level of mutual fund transaction costs, calculated as the average of the sum of front-end and back-end.

[60] The authors measure portfolio risk as either the standard deviation of fund return or tracking error.

would have a concave-convex form, being concave in its leftmost portion referring to poor performing funds, while convex in its rightmost part representing better performing funds. In the context of our study, we expect the form of flow-performance relationship for more sophisticated institutional investors to be closer to the one implied by academic findings. While, in line with previous studies investigating flow-performance relationship for individual investors, we expect the relationship to have a convex form.[61]

Studies of fund selection posit that individual investors face substantial search costs and are less informed than institutional investors. Sirri and Tufano (1998) suggest that search costs have an important impact on investment decisions of individual mutual fund investors. The authors document that high performance seems to be most salient for funds which exert higher marketing efforts as measured by high fees. Media attention, reducing investor search costs, is positively associated with fund flows. Barber, Odean and Zheng (2003) find that mutual fund investors are influenced by salient, attention-grabbing information. They note that investors are more sensitive to salient in-your-face fees, like front-end loads and commissions than operating expenses; they are likely to buy funds that attract their attention through exceptional performance, marketing, or advertising. Moreover, they do not observe any significant relationship between annual flows and fund operational expenses. They explain this result by a positive relationship between fund advertisement efforts and flows, which cancels out the negative effect of the fund expense ratio, embedding advertisement costs. In line with this result, Babalos, Kostakis and Philippas (2009), examining Greek mutual funds, find no relationship between fund expenses and flows. In contrast, Ivkovich and Weisbenner (2009) find that individual investor divestment decisions are sensitive to the fund expense ratio. Presumably, individual investors can be expected to care more for expenses associated with their participation in mutual funds for the simple reason that, in contrast to institutional investors, they pay all the expenses out of their own pocket. For the same reason institutional investors can be expected to be less sensitive to the price of service, but ready to pay more for higher quality or more convenient service.

Simultaneously, individual fund investors may attempt to reduce search cost using publically available information such as historical performance of a benchmark. For instance, individual investors may be expected to evaluate relative fund performance with respect to such

[61] See Sirri and Tufano (1998), and Del Guercio and Tkac (2002).

benchmarks as market indexes or IOC.[62] Another reason to expect individual investors to use benchmarks is the simplicity of the way one can establish whether a fund outperforms its category or not. Such performance evaluation does not require advanced knowledge in finance. Findings of Ivkovich and Weisbenner (2009) support this idea revealing that flows of individual investors into mutual funds are positively related to fund relative performance with respect to its IOC.

While the relevance of performance measure in prediction of fund return is questionable, institutional investors, who can use more complex performance measures due to higher sophistication level, can be expected to use such straightforward estimates less. Benchmarks, however, can have an important influence on fund evaluation process of institutional investors as well. According to the argument of Lakonishok et al. (1992) and Del Guercio and Tkac (2002), institutional investors, in an attempt to reduce their job risk, evaluate fund managers with respect to benchmarks. Their argument can be constituted as follows. The job and the reputation of the corporate insider responsible for allocation of corporate money, are directly affected by the performance of the entrusted money. Thus, he may prefer strategies where blame can be easily readdressed to others and his decisions can be defended ex-post. For instance, the corporate treasurer's office may delegate the money management to external managers and hire consulting firms to select managers, in an attempt to reduce responsibility in the case of poor performance (Lakonishok at al. (1992)). In addition, although good performance of a money manager, with respect to a market benchmark, may serve as a convincing explanation for the choice of manager, corporate insiders may evaluate fund managers with respect to benchmarks (Del Guercio and Tkac (2002). Furthermore, institutional investors, who seek to reduce the cost of manager's bets deviating from the benchmark, pay high attention to tracking error reflecting volatility of managed portfolio from the benchmark. Thus, client attention to tracking error can be interpreted as the result of agency problems because it focuses on the cost of manager bets that deviate from the benchmark, while ignoring the potential benefit in terms of increased return. Empirical findings of O'Connell and Teo (2004) support this argument, providing evidence of highly asymmetric response of institutional investors to gains and losses. Investigating currency contract trade of institutional investors, the authors show that dramatically

[62] Mutual funds usually categorized according to investment objective or investment style they follow. Thus, style performance represents a benchmark in evaluation mutual fund performance (Brown and Goetzmann (1997)).

reducing risk in anticipation of losses, institutions only slightly increase risk in anticipation of gains. Thus, we expect institutional investors to punish fund managers with high tracking error by withdrawing assets from their funds.

Based on prior literature, we also expect to find differences in attitude of individual and institutional investors to momentum exposure of fund. The momentum phenomenon implies that well performing stocks tend to continue performing well (Jegadeesh and Titman (1993)).[63] Sapp and Tiwari (2004), investigating the "smart money" effect for a broad sample of U.S. domestic equity funds, speculate that investors tend to allocate their money into ex-post best-performing funds. Furthermore, past best-performers inevitably disproportionally hold ex-post best-performing stocks. Thus, relocating their money into past winners, investors inadvertently benefit from momentum returns on winning stocks. However, investigating the hypothesis empirically, the authors conclude that higher exposure to the momentum factor does not make a fund more popular, reporting a positive while insignificant relationship between fund momentum exposure and subsequent quarter flows. Since individual investors represent the majority in the sample investigated by Sapp and Tiwari (2004), this finding rather reflects the attitude of individual investors to fund momentum exposure. In contrast, Goetzmann and Massa (2002) document momentum behavior for index fund investors. Contributing to this discussion, Wermers (1997) shows that use of momentum investment strategy by mutual fund managers is one of the main reasons for fund performance persistence, claiming that momentum trading funds succeed consistently to outperform their peers. In his later study, Wermers (2003) investigates holdings of fund portfolios and shows that fund managers who have recently done well tend to invest a considerable portion of new money in the recently winning stocks in attempt to continue to perform well. On the contrary, managers of poorly-performing funds are reluctant to sell underperforming stocks. According to this logic, it is reasonable that investors seek out funds that consistently implement momentum strategy. Moreover, investor preference for momentum trading funds could explain observed momentum trading behavior of mutual fund managers.[64] Furthermore, Nofsinger and Sias (1999) document that institutional investors are momentum traders, arguing that stock return momentum is a main reason for herding behavior, observed among institutional investors. Thus, we expect that institutional fund investors,

[63] Jegadeesh and Titman (1993) document that part of the abnormal returns generated by portfolio combined of "winner" stocks in the first year disappears in the following two years.
[64] See, for example, Brown, Wei and Wermers (2008), and Wermers (1997).

compared to investors of retail funds, demonstrate stronger preference for funds with higher momentum exposure.

The mutual fund literature documents persistence in fund flows. Investigating Israeli equity mutual funds, Ben-Raphael, Kandel and Wohl (2009) document that fund flows are positively auto-correlated. Examining flows of U.S. equity funds, Cashman, Deli, Nardari and Villupuram (2007) document evidence of high persistence in monthly mutual fund flows. While flow persistence attributes herding behavior, prior literature finds this tendency to be stronger for institutional investors. For example, Nofsinger and Sias (1999) show that trading stocks institutional investors tend to follow each other's trades and their own lag trade of securities. Sias (2002) provides evidence for herding behavior of institutional investors, reporting positive relationship between institutional investors' demands for securities over succeeding quarters. Thus, we expect to find stronger persistence in flows of institutional funds.

Finally, to account for possible differences in investor behavior across the business cycle, we examine flow patterns of each fund type separately for expansion and recession periods.[65] This examination is especially valuable in the light of findings of prior literature documenting that mutual fund flows are not time invariant and tend to change with market conditions. Edelen and Warner (2001) and Boyer and Zheng (2008) show that market conditions affect mutual fund flows, documenting a positive relationship between flows into U.S. equity mutual funds and market returns. Studies of Birnbaum, Kallberg, Koutsoftas and Schwartz (2004) and Cederburg (2008) reveal that mutual fund investor behavior changes across the business cycle. Birnbaum, Kallberg, Koutsoftas and Schwartz (2004) document reluctance of both retail and institutional investors to withdraw their funds in bearish market conditions. Cederburg (2008) finds that investors demonstrate strong return chasing behavior during expansions, while they do not chase returns during recessions.[66] Moreover, adverse market conditions may erase attractiveness of funds following momentum strategies. Thus, documenting positive relationship between fund net cash flow and fund momentum exposure, Cederburg (2008) finds that this relationship is weaker during recessions. The author explains this result by higher investors' concern of exposure to aggregate risks during recession than during expansion periods.

[65] Following existing literature investigating flows and performance of mutual funds across the business cycle, we adopt NBER dates of expansion and recession months to define the business cycle (See for examples Moskowitz (2000) Kosowski (2006) and Cederburg (2008)).
[66] Cederburg (2008) uses NBER business cycle dates to define recession and expansion periods.

Simultaneously, a number of papers report variation of mutual fund performance over the business cycle. Moskowitz (2000) notes that mutual funds perform better during recessions than during expansions. Expanding on this subject, Kosowski (2006) reveals that evidence on mutual fund underperformance stems from expansion periods, while during recessions mutual funds show significantly positive alpha.[67] Accordingly, mutual funds seem to perform better when investors need it the most. Moreover, recession periods appear to be the best time to profit from predictability of mutual fund managers' skills. This being the case, we would expect investors to seek more for alpha during recession periods than during expansions. Moreover, more sophisticated investors would be expected to exhibit a stronger priority for fund risk-adjusted performance.

In addition, for investors of retail funds, the effect of fund expense ratio on flows may be expected to differ over the business cycle. Experiencing wealth depreciation, individual investors, presumably, are more sensitive to costs associated with their participation in mutual funds during recession periods than during expansions.

4.4 Data Descriptions

4.4.1 Sample Descriptions

We collect data from the CRSP Survivor-Bias Free US Mutual Fund Database. Our sample comprises of all open-end domestic equity mutual funds existed at any time during the period January 1999 to May 2009 and for which values of monthly total net asset are reported by CRSP. Further, we exclude specialized funds, sector funds, balanced funds and international funds, since risk factors of these funds may differ from risk factors driving the performance of other equity mutual funds. We use the Lipper objective codes provided by the CRSP to assign investment style classification. Thus, we distinguish three investment styles: growth, value, and core. Each of the styles is subsequently broken down by market capitalization into small, medium, large or multiple types. Thereby, we construct investment objective categories (denoted

[67] Both authors – Moskowitz (2000) and Kosowski (2006) – determine recession and expansion periods according to corresponding definition of NEBR.

as IOC). For each fund, we determine investment style as of the date of the last fund observation in our sample.[68]

We treat fund-entity as is denoted by CRSP. More specifically, each fund represents either a share class, thereby representing only a part of the fund assets, or a fund representing an entire portfolio. Our final sample contains 11,710 fund-entities comprising 818,530 fund-months. It includes 4,004 fund-entities as of January 1999 and 7,421 fund-entities as of May 2009 aggregating to \$2.13 trillion and \$2.51 trillion correspondingly.[69]

4.4.2 Classification funds into retail and institutional

We categorize funds as institutional if CRSP designates them as such. Starting in 1999, the CRSP database includes a variable that identifies whether a fund represents institutional or retail type. We use this year as a starting point in our investigation. As mentioned in the previous section, explicit division of funds into institutional and retail, represents relatively recent trends, starting in early 1990s.

CRSP derives institutional/retail identifier from Lipper, and assigns funds as institutional if they fall in Lipper's "Institutional" or "Bank Institutional" categories. More specifically, Bank Institutional funds are considered funds that are primarily offered to clients, agencies and fiduciaries of bank trust departments, commercial banks, thrifts, trust companies, or similar institutions. The bank, bank affiliate or subsidiary acting as advisor or, in some cases, sub-advisor for the funds, and the funds are typically marketed as a bank product. Institutional funds are primarily targeted at organizations and institutions, including pension funds, 401k plans, profit sharing plans, endowments, or accounts held by institutions in a fiduciary, agency or custodial capacity.

Note that this classification may not be a precise identifier of investor type. For instance, the final investment decision of 401k plans' participants is taken by an individual investor, while their capital flows may combine flows of either an institutional or a retail fund. Nevertheless, it

[68] According to Chan, Chen, and Lakonishok (1998), mutual funds, in general, tend to be consistent in their investment objectives.

[69] According to ICI Mutual Funds' Fact Book 2009, of the U.S. mutual funds' total of \$9.6 trillion assets under management as of the end of 2008, 30% (\$2.9 trillion) was accounted for domestic equity mutual funds. In our final sample, total assets of funds aggregates to \$2.4 trillion at the end of 2008, thereby representing about 83% of the 2008 domestic equity mutual fund assets.

seems reasonable to assume that the classification of funds into retail and institutional implies differences in investor composition of the two types of fund. In particular, the overwhelming majority of retail fund investors apparently are regular individuals. At the same time, institutional investors, if participating in mutual funds, can be expected to invest in institutional funds. Furthermore, presumably more sophisticated institutional investors influence flows of institutional funds, while flows of retail funds are determined by investment decisions of unsophisticated – individual investors.

4.4.3 Summary statistics

Table 4.1 contains descriptive statistics for the mutual funds of both samples. Therefore, Panels B and C provide corresponding statistics for the retail fund and the institutional fund samples respectively. For purposes of comparison, we also report corresponding statistics for the sample of all funds (Panel A).

The average monthly net cash flows (described in this section below) into funds are positive for retail and institutional funds. However, the average monthly net cash flow of institutional funds is nearly four times higher than that of retail funds ($1.73 million and $0.44 million correspondingly). If we normalize net cash flow by fund TNA of the prior month, the average normalized monthly cash flows are much more similar for both types of funds. [70]

As reported in Table 4.1, retail funds are on average bigger than institutional funds. Thus, the average retail fund in our sample has $505 million under management compared to $247 million managed by the average institutional fund. Presumably, the observed difference in average size is the result of the size difference between the largest retail and institutional funds. More specifically, the largest institutional fund in our sample is roughly half the size compared to the largest retail fund, managing $48 billion and $97 billion respectively. At the same time, the median fund size is almost the same: $29 million for retail funds compared to $27 million for institutional funds.

In addition, Table 4.1 shows that the average expense ratio is considerably lower for institutional funds than for retail funds. In particular, the average expense ratio for institutional fund (1.02% per year) is 60 percentage points lower than the average expense ratio for the retail

[70] Average monthly normalized cash flow for retail fund is 1.82%, and 2.13% for institutional fund.

fund (1.62% per year). While expense ratios and maximum front-end load fees are considerably higher for retail funds, the turnover ratio is similar for both samples.[71]

Furthermore, institutional funds in our sample seem to perform slightly better at unadjusted and risk-adjusted basis. Lower brokerage commissions and expenses, characterizing institutional funds, is one of possible sources of return difference.

In addition, tracking error – a measure of diversifiable risk – appears to be lower for institutional funds, indicating that the institutional fund manager, on average, tends to deviate less from the market.

[Please insert Table 4.1 about here]

To start working with our flow data at the fund-month level, we eliminate fund-months without records for fund total net asset value. This leaves us with 817,423 fund-months, out of which 576,975 are retail fund-months and are 240,448 institutional fund-months. In addition, we exclude fund-observations with 1st and 99th flow percentile, so that highly unusual flows do not drive our results. More specifically, exceptionally noisy flow data can attribute very young funds or funds about to be closed down.

4.4.4 Measurement of Flows and Performance

We define normalized cash flows as the percentage growth in fund assets, net of appreciation. We calculate them as:

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1+R_{j,t})}{TNA_{j,t-1}}. \tag{1}$$

Here $Flow_{j,t}$ denotes the monthly normalized cash flows for fund *j* during month *t*. $TNA_{j,t}$ refers to the total net assets at the end of month *t*, $R_{j,t}$ is the fund's return for month *t*. The estimate of normalized cash flows expressed in equation (1) implies that existing fund investors fully reinvest their dividends. In addition, the estimate assumes that all the new money is invested at the end of month. As noted in previous studies, normalized cash flows may be

[71] Expense ratio for retail funds is 1.62%, and 1.02% for institutional funds. Maximum front-end load fee is 3.40% for retail funds, and 1.50% for institutional funds.

preferable when dollar flows are positively related to fund size, whereby larger funds attract higher flows regardless of performance (Gruber (1996)).

The performance of mutual funds can be measured in different ways. Since our goal is to reveal which measures are important to investors of each type of funds, we select measures which are available to investors of both types of funds, and can be considered when making their investment decisions. In particular, we use historical raw returns estimated at different lengths and horizons. This assumption is built on evidence of chasing raw return documented by the previous literature. Based on the same logic, we employ relative return to other funds with the same IOC. In addition, we include performance measures considered sophisticated, such as tracking error and a number of risk-adjusted measures including Jensen's, Fama-French, and Carhart alphas. Those measures are expected to be especially important to more sophisticated investors of institutional funds. Furthermore, we include a fund momentum loading factor. Considering well-documented momentum-following behavior, attributing institutional investors, we expect investors of institutional funds to exhibit this tendency as well. All of those measures are lagged, so as to be observable by investors when an investment decision has to be made.

4.5 Analysis and Results

4.5.1 The determinants of fund flows: institutional versus retail funds

As mentioned earlier, differences in clientele profile imply differences in fund selection criteria considered by investors of retail versus institutional funds. In this section, we examine those differences using linear regression framework, as suggested by Del Guercio and Tkac (2002).[72] In particular, we pool all observations with monthly normalized cash flows as a dependent variable and a number of lagged performance and non-performance measures as explanatory variables. More specifically, performance measures include: fund raw return, relative performance of the fund with respect to the average performance of the style to which this fund is related, the momentum factor loading of the fund, fund risk-adjusted returns, and tracking error. The set of non-performance variables includes the natural logarithm of fund total

[72] To test robustness of our results to alternative methodologies, we redo the analysis following the Sirri and Tufano's (1998) approach. In particular, we first estimate cross-sectional regression for each month, and then estimate coefficients and t-statistics as in Fama and MacBeth (1973). We confirm that the results obtained based on the described above approach of cross-sectional regression estimated for each month are qualitatively similar to the results obtained using pooled time series cross-sectional regression reported in the paper.

net assets, the net cash flows of the fund estimated as a dollar change in fund total assets, net of appreciation, the normalized cash flows of the IOC to which the fund belongs, fund turnover and expense ratios, and fund age scaled in months. Following Del Guercio and Tkac's (2002) methodology, we also include a set of time-style interaction variables, one for each combination of month and style. For instance, G200202 variable takes value one if this observation relates to growth style fund in February 2002, and zero otherwise. The time component of the interaction dummy variable captures any cross-sectional correlations in the observations which could emerge due to differences in average flows across months of the sample. The style component accounts to the fact that in any given month, funds with different IOCs may experience average flows that are significantly different from these of other styles. Thereby, adding a time-style interaction dummy reduces the above explained sources of residual dependence, increasing precision of the estimates. Furthermore, to correct for heteroskedasticity, we cluster standard errors by funds. To estimate the corresponding coefficients for investors of institutional and retail funds separately, we interact each of the performance and non-performance explanatory variables with fund type dummy variables. In particular, we include both sets of interactions: the interaction of each of the explanatory variables with the retail fund dummy, which gets value one if an observation relates to flows of retail funds and zero otherwise, and the interaction with the institutional fund dummy, getting value one if an observation is related to an institutional fund.

To estimate the difference in effect of each of those variables on flows between retail and institutional funds, we specify a separate regression including a set of explanatory variables with and without interaction with the institutional fund dummy. Thus, the coefficients of the variables with the interaction represent the difference in effect of corresponding variable on flows of institutional versus retail funds, and t-statistics of those coefficients reflect statistical significance of the differences.

Formally, the regression equation, which estimates effect of the variables on flows of each type of fund, has the following form:

$$Flow_{j,t} = \beta_0 + \gamma_1' P_{j,t} \times R_j + \gamma_2' NP_{j,t} \times R_j + \beta_1 I_j + \gamma_3' P_{j,t} \times I_j + \gamma_4' NP_{j,t} \times I_j + \gamma_5' TS_{j,t} + \varepsilon_{j,t}, \quad (2)$$

where $P_{j,t}$ and $NP_{j,t}$ are vectors of the described above performance and non-performance measures respectively . More specifically, performance measures include the 1st lag of a dummy variable for within style best performing fund getting value 1 if fund monthly return is higher than return of its style in corresponding month and zero otherwise, the 1st lag of fund's monthly raw return, the momentum (UMD) loading of fund calculated over the previous 36 month of fund return, fund's Jensen's alpha calculated over the previous 36 months of fund return, fund tracking error which is the standard deviation of the residuals from the regression of fund excess return over previous 36 month and market portfolio excess return. Non-performance measures comprise the logarithm of fund total net assets estimated to the end of the previous month, the 1st lag of fund's monthly net cash flow, monthly normalized cash flow of fund's IOC, expense ratio as at the end of the previous month estimated as the percentage of total investment that shareholders pay for the fund's operating expenses and turnover ratios as at the end of the previous month defined as a minimum of aggregate purchases or sales of securities during the year, divided by average fund total net assets, and time-style interaction dummies. R_j and I_j are dummy variables to retail and institutional fund respectively, and $TS_{j,t}$ is a vector of time-style dummy interactions constructed for each combination of month and style.

Table 4.2 reports results of the regression specified by equation (2). Specification (1) in Panel A of Table 4.2 contains results for all funds in our sample. Specification (2) in Panel B summarizes estimates of regression specification including fund type interactions terms. The last column in the table reports differences between coefficients of the corresponding variable of institutional versus retail funds. As mentioned above, our set of performance measures includes fund-monthly absolute return as at the end of the previous month, a dummy variable indicating monthly relative performance of fund, with respect to its IOC, getting value one if fund return exceeded average return of all funds in our sample, belonging to the same investment category as the fund, and zero otherwise, the momentum (UMD) loading calculated over the previous 36 months of fund return, fund's Jensen's alpha calculated over the previous 36 months of fund return, and fund tracking error, measured as the standard deviation of the residuals from the regression of fund excess return over the previous 36 months on excess return of market portfolio.

[Please insert Table 4.2 about here]

Overall, the results are consistent with our expectations. Coefficients of the lagged absolute returns are positive and significant for both types of funds, indicating that both retail and institutional fund investors chase past return (Panel B of Table 4.2). More specifically, controlling for the rest, an additional 1% of monthly raw return implies an increase of 7 percentage points in the next month normalized cash flows of retail fund, and an increase of almost 5 percentage points in succeeding month normalized cash flows of institutional fund. This result is in line with earlier literature, documenting return chasing behavior of individual investors.[73] Moreover, more sophisticated investors of institutional funds also demonstrate significant return chasing. Consistent with the Lakonishok et al. (1992) argument, this finding indicates that investment decisions of institutional investors may be affected by agency conflict. In particular, an institution may entrust money management to outside managers in an attempt to avoid responsibility in the case of poor performance. Thus, the fund selection process would be mainly based on past returns. For instance, the corporate insider responsible for money allocation can easily switch between money managers, relocating the money from a poorly performing manager to a manager who has done well in the past. This way the money manager selection process is based mainly on past performance (Lakonishok et al. (1992)).

Yet, as expected, return chasing tendency appears to be significantly weaker for more sophisticated investors of institutional funds compared to this demonstrated by less sophisticated investors of retail funds. To distinguish whether the observed difference depends on the frequency of the return estimate, we repeat the analysis for returns measured at a quarterly, semi-annually, and annually basis. The results of those specifications confirm that, return chasing behavior is found to be significantly stronger for retail fund investors, independently of the frequency at which the returns are measured.

Fund Jensen's alpha is found to be positively and significantly related to normalized cash flows of both retail and institutional funds. Thus, both more sophisticated investors of institutional funds and unsophisticated investors of retail funds, consider risk-adjusted performance selecting funds. Consistent with the differences in investor characteristics, the result shows that investment decisions of institutional fund investors are influenced much stronger by Jensen's alpha. While institutional fund investors, considered to be more sophisticated investors, are expected to use more complex quantitative measures, it is less obvious to expect unsophisticated retail investors to employ those measures. According to Del Guercio and Tkac (2002), high correlation of Jensen's alpha with widely available fund valuation measures such as

[73] See, for example, Palmiter and Taha (2008), Del Guercio and Tkac (2002), Capon, Fitzsimons and Prince (1996), and Sirri and Tufano (1992).

Morningstar ranking can explain this result. Nevertheless, when we repeat the analysis replacing Jensen's alpha with Fama-French alpha and subsequently with Carhart alpha, the results, qualitatively, stay the same.[74] Therefore, our results indicate that while institutional funds investors rely more on quantitatively sophisticated performance measures, investors of retail funds when making their investment decisions, consider those measures as well. Possibly, the fact that a considerable part of individual investors use the help of financial advisers (ICI fact book 2009), who place great emphasize on various advanced performance measures (Jones, Lesseig and Smythe (2005)) is one of the reasons for this findings.

Furthermore, we find a significant positive relationship between fund momentum (UMD) loading and normalized cash flows. This is in contrast to findings of Sapp and Tiwari (2004), reporting positive while insignificant relationship between fund momentum exposure and subsequent quarter normalized cash flows. Given the findings of Wermers (1997, 2003), who suggests that momentum trading is one of the main reasons for performance persistence of top performing funds, it is reasonable to investors to seek out funds that consistently implement momentum strategy. If so, more sophisticated investors can be expected to pay higher attention to fund momentum exposure. Our results support this statement. In particular, while the momentum exposure is found to be significant for retail as well as for institutional funds, the effect appears to have a stronger impact on flows of institutional funds. This result is also consistent with prior literature, documenting momentum following behavior, primarily for institutional investors.[75]

The coefficient of fund prior month normalized cash flows is positive and significant for both types of funds. Thereby, in line with existing literature, our results show persistence in fund

[74] In addition, we repeat the analysis replacing Jensen's alpha with fund appraisal ratio – a measure of fund manager's stock picking ability estimated as a ratio of fund Jensen's alpha to the fund unsystematic risk or standard deviation of residuals from the market model. Accordingly, appraisal ratio can be classified as a quite complex quantitative measure of fund manager performance. Thus, more sophisticated investors – whom in our sample represent investors of institutional funds – can be expected to pay higher attention to this manager performance measure. In line with this prediction, the results of the analysis show that flows of institutional funds are stronger related to the ratio than flows of retail funds. Nevertheless, the results indicate that less sophisticated investors of retail funds consider fund appraisal ratio when making their investment decisions as well. This result is rather expectable given high correlation between appraisal ratio and Jensen's alpha (the correlation between fund appraisal ratio and Jensen's alpha in our sample is equal to 0.76).

[75] See, for example, Jegadeesh and Titman, (1993), Nofsinger and Sias (1999), Grinblatt and Keloharju (2001), Froot and Teo (2004), Sias (2004), and Gallo, Phengpis and Swanson (2008).

flows.[76] The influence of past fund flows appears to be more pronounced for institutional funds. This result supports the findings of Nofsinger and Sias (1999), who document stronger herding behavior for institutional investors trading stocks.

The results show a significant negative relationship between fund normalized cash flows and its expense ratio. This finding is in line with the results of Ivkovich and Weisbenner (2009), revealing sensitivity of fund outflows to expense ratio. Notably, retail fund investors exhibit much stronger sensitivity to fund expenses than institutional investors. The coefficient of expense ratio variable for retail investors is more than twice higher than this for institutional fund investors. Thus, controlling for the rest of characteristics, a retail fund with expense ratio higher in 1%, on average experiences almost 1.10% lower inflows than its competitors with the lower expense ratio. While, an institutional fund with corresponding high expense ratio has inflows that are only 0.48% lower compared to the flows of its institutional peers with the lower ratio. Considering that institutional investors are supposed to be better informed and such fund characteristics as expense ratio are more accessible to institutional investors, this result is rather surprising. Moreover, according to Barber, Odean and Zheng (2003), since retail investors face substantially higher search costs and are less informed than institutional investors, they are more likely to buy funds attracting their attention through advertising, even although advertising efforts increase fund expense ratio. Probably, the fact that, in contrast to institutional investors, individuals invest on their own behalf, makes them pay greater attention to costs associated with the investment. While, for institutional investors costs related to investment, do not play such an important role. Another possible reason for the observed disparity in the effect of fund expenses, may be difference in level and quality of services required by each type of investors from funds. Apparently, being less sensitive to price of service (due to the fact that they do not invest their own money), institutional investors are ready to pay for a higher quality or more convenient service.

In addition, our results reveal that fund normalized cash flows have significant relationship with relative performance of fund with respect to benchmarks. More specifically, keeping the rest of variables the same, retail funds outperforming their IOC in a given month, on average experience 0.18% higher inflows in the subsequent month. Correspondingly,

[76] See, for example, Hendricks, Patel, and Zeckhauser (1993), Del Guercio and Tkac (2002), and Cashman, Deli, Nardari and Villupuram (2007).

institutional funds with performance higher than the performance of their IOC, attract 0.13% more flows than their underperforming peers. This result suggests that the benchmark plays an important role in fund selection process of both types of investors. To test whether the effect of relative fund performance exists for relative performance of lower frequency, we repeat the analysis for quarterly, semi-annually, and annually measured relative fund performance. We find that the effect is present for relative fund performance estimated on lower frequency as well, gradually increasing for performance with the decline of frequency. We suppose that the simple way one can establish whether a fund outperforms its category or not, together with wide availability of performance data for IOC, may explain why investors use IOC outperformance criterion when evaluating funds. While the relevance of this performance measure in prediction of fund return is questionable, institutional investors, who can use more complex performance measures due to a higher sophistication level, use such straightforward estimates less.

The important influence of the benchmark is also reflected in a significant relationship between normalized cash flows and fund tracking error, indicating to which extent funds deviate from market benchmarks. The results show, that investors punish fund managers deviating from the market benchmark by withdrawing money, while institutional investors respond to high tracking error much more aggressively. In particular, the coefficient representing the effect of tracking error for institutional funds (-0.59) is three times higher than the corresponding coefficient for retail funds (-0.21%). This result is consistent with agency conflict interpretation suggested by Lakonishok et al. (1992) and Del Guercio and Tkac (2002). Their argument can be constituted as follows. The job and the reputation of the corporate insider, responsible for allocation of corporate money, are directly affected by the performance of the entrusted money. Thus, he may prefer strategies where blame can be easily readdressed to others and his decisions can be defended ex-post. For instance, the corporate treasurer's office may delegate the money management to external managers and hire consulting firms to select managers in attempt to reduce responsibility in the case of poor performance (Lakonishok at al. (1992)). In addition, since good performance of money managers, with respect to a market benchmark, may serve as a convincing explanation for the choice of manager, corporate insiders may evaluate fund managers with respect to benchmarks (Del Guercio and Tkac (2002). Following this line of reasoning, institutional investors, who seek to reduce the cost of manager's bets deviating from the benchmark, pay high attention to tracking error, reflecting volatility of managed portfolio from the benchmark. Empirical findings of O'Connell and Teo (2004) support this argument, providing evidence of highly asymmetric response of institutional investors to gains and losses. The authors show that, institutional investors dramatically reducing risk in anticipation of losses but only slightly increase risk in anticipation of gains.

4.5.2 Benchmark

However, not only the extent to which fund return deviates from market return, and whether or not fund manager bets benchmark affect fund flows, but also the magnitude of the excess return of funds on benchmark return may influence flows (see, for example, Del Guercio and Tkac (2002)). Thus, we continue with closer investigation of the effect of the benchmark on fund flows, using IOC and S&P 500 index as benchmarks.[77] Following Del Guercio and Tkac (2002) methodology, besides testing influence of direct event of beating benchmarks, we examine the effect of fund absolute excess return on benchmark returns. In addition, we account for the asymmetry in the effect for well and badly performing funds, estimating the effect of the performance variables separately for funds performing better and worse than the benchmark. For this purpose, we include the following dummy variables in the analysis: $Out_{j,t-1}$ getting value one if in the previous month fund raw return is higher than raw return of benchmark, and zero otherwise, and $Under_{j,t-1}$ equals to one if in the corresponding month raw return of fund is lower than raw return of the benchmark;

Thus, considering investment objective category (IOC) as a benchmark, we specify the following regression equation:

$$Flow_{j,t} = \beta_0 + \gamma_1' Out_{j,t} + \gamma_2' P_{j,t} \times Out_{j,t-1} + \gamma_3' P_{j,t} \times Under_{j,t} + \gamma_4' C_{j,t} + \gamma_5' TS_{j,t} + \varepsilon_{j,t}, \qquad (3)$$

where $Out_{j,t}$ is a dummy variable equal to one, if fund raw return in the previous month is higher than raw return of funds' IOC in the corresponding month, and zero otherwise; $Under_{j,t}$ is a

[77] Investment objective category is commonly considered as a benchmark in evaluation of mutual funds. Information regarding performance of investment objective category and relative performance of fund with respect to its category is upgraded at high frequency and publically available. Simultaneously, S&P 500 index can be considered as a proper benchmark, given the fact that our sample consists solely of U.S. domestic equity funds. In addition, previous studies examining the effect of benchmark on flows of mutual funds document that mutual fund investors use S&P 500 index as benchmark (Del Guercio and Tkac (2002)). We do not report results of the analysis using S&P Index as a benchmark. Nevertheless, we confirm that those results are qualitatively similar, and will be provided by the authors upon request.

dummy variable, which is equal to one, if in the corresponding month raw return of fund is lower than raw return of fund's IOC; is a vector of the lagged in one month performance measures including fund excess returns defined as a difference between contemporaneous raw returns of fund and return of its IOC, Jensen's alpha, and tracking error; $C_{j,t}$ is a vector of control variables comprising the natural logarithm of fund total net assets estimated to the end of the previous month, the lagged monthly net cash flows of the fund estimated as a dollar change in fund total assets, net of appreciation, the normalized cash flows of the IOC to which the fund belongs, fund turnover and expense ratios as of the end of previous month, and fund age scaled in months. Similarly to the previous analysis expressed by equation (2), we interact each of the explanatory variables with fund type dummies. Thus, R_j and I_j are dummy variables to retail and institutional fund respectively, and $TS_{j,t}$ is a vector of time-style dummy interactions. The statistical significances of differences in corresponding coefficients for institutional and retail funds are estimated based on an approach similar to the one implemented in the previous analysis.

Table 4.3 presents the results of the regression analysis. Specification (1) in Panel A of Table 4.3 reports the results for the sample of retail funds, Specification (2) in Panel B – the results for the sample of institutional funds. Consistent with the results documented in Table 4.2, the coefficient on the outperformance IOC dummy is positive for both types of funds, while, the effect is found to be economically and statistically significant only for the retail fund sample. This result confirms that, the fact whether fund manager beats IOC, positively affects future period flows.

[Please insert Table 4.3 about here]

The positive and significant coefficients of fund positive excess return on the return of IOC, found for both types of funds, show a significant relationship between normalized cash flows and the magnitude of fund's excess return on the return of its category. More specifically, outperforming its category by 1 additional percent, the retail fund can expect the next month flows to be 23 percentage points higher. In the case of institutional funds, an increase of 1 percent in outperformance of investment category predicts subsequent month normalized flow to be 18 percentage points higher. Thus, economic significance of the effect of positive excess return is merely similar among retail and institutional funds. Notably, our results do not detect any significant effect of negative excess return on flows of institutional funds: coefficient for interaction of fund excess return on return of its category, with dummy for underperforming funds, is insignificant for institutional funds. The coefficient for retail funds is negative and significant, indicating that a higher gap between fund performance and the performance of the fund's ICO is associated with higher outflows from the fund in the succeeding month.

In addition, the coefficient of tracking error for outperforming institutional funds is significantly smaller than this coefficient for underperforming institutional funds, meaning that institutional fund investors' punishment for deviation from the market is considerably weaker for managers outperforming their investment categories. This is in contrast to retail funds, for which negative effect of tracking error for both outperforming and underperforming funds is merely the same. Moreover, the influence of tracking error on flows of outperforming and of underperforming retail funds is considerably smaller than that for corresponding institutional funds. This result supports the findings of our previous analysis, indicating that institutional fund investors, compared to investors of individual funds, pay much higher attention to tracking error reflecting volatility of managed portfolio from benchmarks. At the same time, the result indicates that investors of both retail and institutional funds punish for deviation from the market even managers outperforming their investment category.

Further, the results reveal that for retail funds outperformance of investment category significantly strengthens the effect of Jensen's alpha: the coefficient of Jensen's alpha is 55 percentage points higher for funds outperforming their IOC, and that difference is statistically significant. In contrast, the difference in the effect of Jensen's alpha on fund flows between the outperforming and the underperforming institutional funds comprises only 20 insignificant percentage points. This result implies that flow-performance relationship for retail and institutional funds may have a different form. Further in this chapter, we proceed with closer investigation of the form of flow-performance relationship for each type of funds.

4.5.3 The form of flow-performance relationship

Differences in investor profile between institutional and retail funds may be reflected in difference of the flow-performance relationship form characterizing each of the fund types. Since, investors of institutional funds are supposed to be more sophisticated, we expect the form of the flow-performance relationship characterizing institutional funds to be more effective.

The extensive literature studying mutual fund performance persistence, documents that persistence in fund return is mostly found among the worst and the best performing funds (see Hendrix, Patel, and Zeckhauser (1993), Ibbotson and Goetzmann (1994), and Berk and Tonks (2007)). According to those academic findings, we would expect more sophisticated investors to punish the worst performing funds through withdrawal of assets from those funds, realizing the likelihood that these funds will continue to perform poorly, while to reward the best-performing funds with higher inflows anticipating that those funds would maintain high returns in the future. In this case, the form of flow-performance relationship would be concave in the part reflecting punishment of worse performers, and convex in its part representing flow-performance relationship among better performing funds.

Researchers studying the flow-performance relationship for mutual funds, however, find the relationship is non-linear and has a convex form, concluding that mutual fund investors indeed allocate more assets in recently best-performing funds, while they do not punish poor performing funds. We suppose that given a higher level of financial sophistication of institutional fund investors, the flow-performance relationship form, for institutional funds, may be closer to the effective one as is implied by the literature.

To test this hypothesis, we apply methodology suggested by Sirri and Tufano (1998). In particular, we examine the relationship between fund normalized cash flows and the rank of various fund-performance measures estimated to the end of the previous month.

A relative performance of each fund is estimated with respect to the relevant performance measure of fund's IOC. A fractional rank of fund ($Rank_{j,t}$) ranges from 0 to 1 and represents its percentile performance relative to other funds with the same IOC in month t. Since we are interested in identifying the potential asymmetric response to good and bad performance, we conduct the analysis using a piecewise linear regression. More specifically, we include five quintile variables indicating fund relative performance ranking. The quintiles ($Qn_{j,t}$) are constructed as following:

$$Q1_{j,t} = Min\left[Rank_{j,t}, 0.2\right],$$

$$Q2_{j,t} = Min\left[Rank_{j,t} - Q1_{j,t}, 0.2\right],$$

$$Q3_{j,t} = Min\left[Rank_{j,t} - Q1_{j,t} - Q2_{j,t}, 0.2\right],$$

$Q4_{j,t} = Min[Rank_{j,t} - Q1_{j,t} - Q2_{j,t} - Q3_{j,t}, 0.2]$,

$$Q5_{j,t} = Min[Rank_{j,t} - Q1_{j,t} - Q2_{j,t} - Q3_{j,t} - Q4_{j,t}, 0.2]. \quad (4)$$

Thus, if fund performance at corresponding month represented 75 performance percentile within its IOC, each of the variables $Q1$, $Q2$ and $Q3$ will get value 0.2; the value of the variable $Q4$ will be equal to 0.15, and $Q5$ will be 0.

To test the flow-performance relationship, we specify the following regression equation[78]:

$$\begin{aligned} Flow_{j,t} = {} & \beta_0 + \beta_1 Q1_{j,t-1} \times R_j + \beta_2 Q2_{j,t-1} \times R_j + \beta_3 Q3_{j,t-1} \times R_j + \beta_4 Q4_{j,t-1} \times R_j + \\ & + \beta_5 Q5_{j,t-1} \times R_j + \beta_6 C_{j,t-1} \times R_j + \beta_7 \times I_j + \beta_8 Q1_{j,t-1} \times I_j + \beta_9 Q2_{j,t-1} \times I_j + \\ & + \beta_{10} Q3_{j,t-1} \times I_j + \beta_{11} Q4_{j,t-1} \times I_j + \beta_{11} Q5_{j,t-1} \times I_j + \gamma_1' C_{j,t-1} \times I_j + \gamma_2' TS_{j,t} + \\ & + \varepsilon_{\ j,t}, \end{aligned} \quad (5)$$

where $Q1_{j,t-1}$, $Q2_{j,t-1}$, $Q3_{j,t-1}$, $Q4_{j,t-1}$ and $Q5_{j,t-1}$ are quintile variables indicating fund relative performance ranking; $C_{j,t-1}$ is a control variables vector comprising the natural logarithm of fund total net assets estimated to the end of the previous month, the lagged monthly net cash flows of the fund estimated as a dollar change in fund total assets, net of appreciation, the normalized cash flows of the IOC to which the fund belongs, fund turnover and expense ratios, and fund age scaled in months. Similarly to the previous analyses, we interact each of the explanatory variables with fund type dummies. Thus, R_j and I_j are dummy variables to retail and institutional fund respectively. $TS_{j,t}$ is a vector of time-style dummy interactions.

Table 4.4 summarizes regression coefficients for different performance measures. Panel A of Table 4.4 reports results for raw return estimated at monthly and annual frequency; Panel B – for risk-adjusted return measured as Jensen and Fama-French alphas. In each panel, specification (1) reports the regression coefficients for all funds in our sample, while specification (2) shows estimates of regression including fund type interaction terms. In line with previous studies, our results confirm a positive relationship between fund normalized cash flows

[78] To test robustness of our results to alternative methodologies, we redo the analysis following the Sirri and Tufano's (1998) approach. In particular we first estimate cross-sectional regression for each month, and then estimate coefficients and t-statistics as in Fama and MacBeth (1973). We confirm that the results obtained based on the above described cross-sectional regression estimated for each month approach are qualitatively similar to the results obtained using pooled time series cross-sectional regression reported in the paper.

and a fund's historical performance, and the form of this relationship is not linear. The results for annual return (reported in Panel A of Table 4.4) show that the coefficients of all performance quintiles are positive and significant. While the flow-performance relationship is positive for all quintiles of monthly return as well, not all of those relationships are found to be statistically significant. Nevertheless, the relationships for the top quintile of monthly return of both types of funds are statistically significant. The results in Panel B indicate similar pattern for risk-adjusted measures: flow-performance relationship is significant and positive for all quintiles as for Jensen's alpha as well as for Fama-French alpha.

[Please insert Table 4.4 about here]

To get a better sense about form of flow-performance relationship for each performance measure, we plot the result of the regression analysis graphically (see Figure 4.3). In particular, in Figure 4.3 for each quintile of corresponding return measure we depict expected change in the monthly normalized cash flows as a function of having performance in a certain performance quintile. For example, the effect of the lowest quintile is expressed by its regression coefficient. While, to estimate the effect of second performance quintile, we sum up coefficients of the first and the second quintiles. As one can note, the flow-performance relationship has a convex form for all performance measures of retail funds, confirming findings of previous papers that, individual investors tend to allocate disproportionally more assets in the better performing funds, but do not punish bad performers by withdrawing assets from those funds. The slope is largest in the rightmost portion of the flow-performance graphs for retail funds, and smallest in the leftmost portion of the graphs.[79] This form implies that investors of those funds tend to allocate disproportionally more into good performers, but do not punish bad performers by withdrawing money. As a result, fund managers, who are typically compensated as a percentage of assets under management, have an implicit incentive to raise the risk of their portfolios in order to increase the chances to be among the winners, without taking a risk of being punished in the case of failure.[80]

[79] We examine statistical significance of the observed convexity/concavity testing significance of difference between coefficients of each two fractional performance quintiles. To test each of the differences, we re-parameterize the original model in such a way that the tested linear restriction $H0$ ($\beta_{Q(N+1)} - \beta_{Q(N)} = 0$) corresponds to a linear restriction of $\beta^* = 0$ form (Verbeek (2000), "A Guide to Modern Econometrics").

[80] See, for example, Brown, Harlow, and Starks (1996), and Chevalier and Ellison (1997).

However, that is not the case for institutional funds. Being merely linear with slight convexity in their rightmost part, the graphs of flow-performance relationship for institutional funds are either linear (for annual raw return and Fama-French alpha) or concave (for monthly raw return and Jensen's alpha; for Jensen's alpha the observed concavity is also statistically significant, at 5% level).[81] These results reveal that in contrast to retail fund investors, institutional fund investors withdraw assets from poor performing funds punishing the worst performers harder, while allocating assets into good performing funds with a preference to the best performers. Thus, our results show that concave-convex form of the flow-performance relationship for institutional funds weakens fund manager incentive to follow the discussed risk-shifting behavior.

[Please insert Figure 4.3 about here]

4.5.4 Investment flows across the business cycle

So far, we have documented determinants of mutual funds' investment flows for retail and institutional funds and how these determinants vary across investors of these two types of funds. However, existing literature suggests that investment flow pattern may change across the business cycle.[82] To account for possible differences in investor behavior across the business cycle, we further compare flow patterns of two types of funds separately for expansion and recession periods using the NBER recession-expansion classification (see Appendix 4.1). We use a regression specification similar to the one expressed by equation (2).

[Please insert Table 4.5 about here]

Table 4.5 reports the results of the analysis. The coefficients of lagged raw returns for both retail and institutional funds are higher for expansion months. In particular, controlling for the rest, additional percent in monthly return predicts a statistically significant increase of 9 percentage points in flows of retail funds and 7 percentage points in flows of institutional funds during expansion. At the same time, similar return growth predicts only an increase of less than 3 percentage points in flows of both types of funds during recession period. These results reveal

[81] The differences indicating in the graphs convexity of flow-performance relationship for retail funds are strongly significant (at 1% level). In contrast, we do not find any significant differences between the coefficients of fractional performance for institutional funds except the concave form observed in the leftmost of the Jensen's alpha graph.
[82] See, for example, Cederburg (2008), and Shrider (2009).

that expansion investors of both types of funds demonstrate much stronger return chasing behavior than recession investors. This finding is in line with the results of Cederburg (2008), who documents that return chasing behavior attributes expansion mutual fund investors rather than recession mutual fund investors.

For retail funds, the coefficient of outperformance IOC is noticeably higher for expansion months. Thus, during expansion flows of the retail fund outperforming its investment category is expected to be 22 percentage points higher than these of the underperforming fund, and the difference is statistically significant. During recession, however, a retail fund outperforming its IOC in the prior month has approximately the same level of flows as its underperforming peer. This indicates that normalized cash flows of retail funds are sensitive to relative performance of fund, with respect to its IOC, only during expansion months. Flows of institutional funds are also found to be significantly related to relative fund performance only during expansion period. In line with the results that we report earlier in this chapter, sensitivity of institutional fund flows to relative fund performance is significantly weaker compared to that of retail funds' flows.

The coefficients of Jensen's alpha estimated for recession are twice higher than the corresponding coefficients for expansion for both types of funds. This result reveals that the effect of risk-adjusted return on fund normalized cash flows is much stronger during recessions. Thus, recession investors pay higher attention to fund alpha. Considering findings of prior literature, suggesting that mutual funds perform – at risk-adjusted basis – at best during recessions, [83] this behavior seems to be rational, and may explain why this tendency is especially pronounced among presumably more sophisticated institutional investors.

In addition, our results indicate that both institutional and retail fund investors tend to punish funds with a higher tracking error through withdrawing assets from those funds during expansions, while institutional fund investors react more aggressively to a deviation of fund manager from the market. In contrast, recession investors of both types of funds do not punish fund managers for higher tracking error. Moreover, normalized cash flows of retail funds appear to be positively related to tracking error during bearish periods.

Further, consistent with the results of Cederburg (2008), we find that exposure of fund to stock momentum has a different influence on fund normalized cash flows during expansion and

[83] See, for example, Kosowski (2006), and Avramov and Wermers (2006).

recession months. We find that for both types of funds, momentum exposure has much stronger influence during expansion periods. Moreover, the results show that momentum-trading institutional funds attract considerably higher inflows than their retail counterparts during expansions, while those funds experience relatively lower flows over recessions. Thus, attractiveness of momentum strategies depreciates during recession periods when the stock market is going down.

Finally, in line with our prediction, the results show that the difference between investors of retail and institutional funds in their sensitivity to fund expense ratio is more pronounced during recessions. This finding is consistent with our argument that individual investors care more for expenses associated with their participation in mutual funds since, in contrast to institutional investors, they pay all expenses out of their own pocket. At the same time, institutional investors, being less sensitive to the price of service, are ready to pay more for higher quality or more convenient service.

4.6 Conclusion

The typical retail fund investor differs noticeably from the typical institutional fund investor in his level of financial sophistication, investment objectives, and search costs.[84] Consequently, criteria that these two types of investors base their investment decision are likely to vary, making investment flow patterns of retail and institutional funds differ too.

In this chapter, we study determinants of mutual funds' investment flows separately for retail and institutional funds, examining how fund selection criteria vary across investors of these two types of funds. Examination of flows at the monthly frequency allows us to get more precise picture of fund flows' dynamic as compared to analysis based on quarterly or annually estimated flows.

We conduct our investigation using complete universe of diversified U.S. equity mutual funds for the period January 1999 to May 2009 in the CRSP Survivor-Bias Free U.S. Mutual Fund Database. We categorize funds into retail and institutional based on the corresponding designation provided by CRSP. Note that this classification may not be a precise identifier of

[84] See, for example, Alexander, Jones and Nigro (1998), Del Guercio and Tkac (2002), and Palmiter and Taha (2008).

investor type. For instance, the final investment decision of 401k plans' participants is taken by an individual investor, while their capital flows may combine flows of either an institutional or a retail fund. Nevertheless, it seems reasonable to assume that the classification of funds into retail and institutional implies differences in investor composition of the two types of fund. In particular, the overwhelming majority of retail fund investors apparently are regular individuals. At the same time, institutional investors, if participating in mutual funds, can be expected to invest in institutional funds. Furthermore, presumably more sophisticated institutional investors influence flows of institutional funds, while flows of retail funds are determined by investment decisions of unsophisticated – individual investors.

We document a number of differences in the investment flow patterns consistent with client attributes. First, we find that customers of institutional mutual funds react more to criteria considered sophisticated. We also find that the observed difference in flow-performance relationship increases during recession periods. On the other hand, flows of retail funds have a stronger relationship with unadjusted performance measures.

Consistently with the empirical findings of previous literature, the flow-performance relationship appears to have a non-linear form.[85] However, the form of this relationship is not the same for flows of retail and institutional funds. While for retail funds, the relationship appears to have a convex form, implying that investors of those funds tend to allocate disproportionally more into good performers, but do not punish bad performers by withdrawing money. For institutional funds, however, the form of flow-performance relationship appears to be convex only in the part reflecting disproportional priority of good performers to the rest of the funds. Conversely, the form is concave in the part reflecting punishment of bad performers. This result implies that investors of institutional funds withdraw assets from poor performing funds punishing the worst performers the hardest, while allocating assets into good performing funds, investing more in the best performers.

Our findings on differences in the form of the flow-performance for retail and institutional funds relationship contribute to the extensive literature on incentives and driver factors of fund manager behavior. The convex shape of the flow-performance relationship, observed for the funds of retail fund sample, implies that "winners take all". As a result, fund

[85] See, for example, Ippolito (1992), and Sirri and Tufano (1998).

managers, who are typically compensated as a percentage of assets under management, have an implicit incentive to raise the risk of their portfolios in order to increase their chances to be among the winners, without taking a risk of being punished in case of failure.[86] At the same time, the observed concave-convex form of the flow-performance relationship for institutional funds may weaken fund manager incentive to follow the discussed risk-shifting behavior.

Further, our results indicate that relative performance of funds, with respect to benchmarks, is an important criterion in fund selection process. Both institutional and retail funds, outperforming their IOC, experience higher flows than underperforming funds. The benchmark appears to have a stronger influence among investors of retail funds. In line with the Guercio and Tkac (2002) findings. The influence of the magnitude of the excess returns on find flows is found to be especially pronounced at the top of the performance distribution.

In addition, we find a significant negative relationship between investment flows and tracking error – a measure of diversifiable risk – for both institutional and retail mutual funds. Thus, both types of investor punish funds with a higher tracking error through withdrawing assets from those funds, and the tendency appears to be much more pronounced for flows of institutional funds. Furthermore, for institutional funds, the influence of tracking error on investment flows is stronger during expansion periods. In contrary, flows of retail funds are, though weaker than institutional flows, negatively related to tracking error during bullish periods and positively related to tracking error during bearish periods.

We also provide evidence suggesting that flows of both types of funds are significantly positively related to fund momentum exposure. Consistent with the literature documenting variation of investor behavior across different market conditions, our results show that momentum-trading institutional funds attract considerably higher inflows than their retail counterparts during expansions, while those funds experience relatively lower flows over recessions.[87]

We document that both institutional and retail funds with higher inflows in the past continue to experience higher inflows in the subsequent periods.[88] Moreover, this effect appears

[86] See for example Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997).
[87] See, for example, Grinblatt and Keloharju (2001), and Glode Hollified, Kacperczyk, and Kogan (2009).
[88] See, for example, Hendricks, Patel, and Zeckhauser (1993), and Del Guercio and Tkac (2002).

to be stronger for institutional funds. This result suggests that institutional fund investors exhibit stronger herding behavior, which is in line with the results reported by previous literature.[89]

Finally, fund expense ratio also appears to have a significant influence on flows of both types of funds. In particular, mutual funds with lower expense ratio experience higher inflows. Retail fund investors demonstrate stronger sensitivity to fund expense ratio, and the difference is even larger during recession periods. Probably, investors of institutional funds – being less sensitive to the price of services – due to the fact that they do not invest their own money – are ready to pay for higher quality or more convenient service.

[89] See for example Nofsinger and Sias (1999), Lakonishok, Shleifer and Vishny (1992b).

4.7 Tables, Figures, and Appendix (Chapter 4)

Table 4.1
Descriptive Statistics for Mutual Fund Sample

The table presents summary statistics on the mutual fund sample obtained from the CRSP Survivor-Bias Free US Mutual Fund Database. The sample includes all U.S. equity mutual funds that existed at any time during January 1999 to May 2009 for which monthly total net assets (TNA) values are available. We exclude sector funds, international funds, specialized funds, and balanced funds. Panel A reports corresponding statistics for all funds. Panel B reports the statistics for the sample of retail funds, Panel C – for the sample of institutional funds. The final sample of all funds consists of 11,710 fund-entities comprising 818,530 fund-months, the sample of retail funds consists of 7,779 fund-entities comprising 577,648 fund-months, the sample of institutional funds consists of 3,931 fund-entities comprising 240,881fund-months. We report statistics for the total net assets for the fund at the end of month, the dollar monthly normalized cash flow (Flowj,t) for fund j during month t is measured as $Flow_{j,t} = (TNA_{j,t} - TNA_{j,t-1} \times (1 + Ret_{j,t}))/(TNA_{j,t-1})$ (In this equation, the terms *TNAj,t-1* and *TNAj,t* represent the total net assets for the fund at the end of month *t-1* and *t* respectively, *Rerj,t* represents the fund's return in month *t*), the dollar monthly net cash flow (NCFj,t) for fund *j* during month t measured as $NCF_{j,t} = TNA_{j,t} - TNA_{j,t-1} \times (1 + Ret_{j,t})$, monthly fund return, fund tracking error which is the standard deviation of the residuals from the regression of fund excess return over previous 36 month and market portfolio excess return, turnover defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA, maximum front-end load, which is the maximum percent charges applied at the time of purchase, and expense ratio defined as the percentage of total investment that shareholders pay for the fund's operating expenses.

	Panel A: All Funds					Panel B: Retail Funds					Panel C: Institutional Funds				
	Mean	Median	25th	75th	St.D.	Mean	Median	25th	75th	St.D.	Mean	Median	25th	75th	St.D.
Monthly TNA (mill.$)	431.84	28.39	4.16	154.95	2571.39	505.05	29.15	4.84	160.72	2952.69	247.02	27.24	2.97	144.12	1134.27
Monthly Normalized Flows (%)	1.96	-0.06	-1.79	2.67	12.01	1.82	-0.21	-1.87	2.46	11.52	2.13	0.25	-1.59	3.06	12.82
Monthly Net Cash Flows (mill.$)	0.88	0.01	-0.62	0.63	23.96	0.44	-0.02	-0.81	0.58	24.09	1.73	0.01	-0.30	0.85	22.94
Monthly Return (%)	0.14	0.09	-1.37	1.64	2.48	0.13	0.08	-1.40	1.64	2.52	0.18	0.13	-1.29	1.65	2.36
Tracking Error	0.017	0.015	0.010	0.022	0.010	0.018	0.016	0.010	0.023	0.010	0.016	0.015	0.010	0.021	0.009
Turnover Ratio (%)	76.47	65.68	34.66	107.98	52.84	76.37	65.32	34.50	107.65	53.13	76.91	66.81	35.01	109.22	52.28
Maximum Front-End Load Fee (%)	3.30	4.56	0.51	5.30	2.29	3.40	4.64	0.75	5.36	2.24	1.50	0.32	0.00	3.53	1.76
Expense Ratio (%)	1.45	1.40	1.04	1.91	0.56	1.62	1.61	1.23	2.04	0.53	1.02	1.00	0.78	1.24	0.39

Table 4.2

Determinants of Normalized Cash Flows: Retail versus Institutional Funds

The table reports the coefficients from pooled time-series cross-sectional OLS regressions of funds' monthly normalized cash flow on the 1st lag of best performer dummy getting value 1 if fund monthly return is higher than return of its style in corresponding month and zero otherwise, the 1st lag of fund's monthly return, the momentum (UMD) loading calculated over the previous 36 month of fund return, fund's Jensen's alpha calculated over the previous 36 months of fund return, fund tracking error which is the standard deviation of the residuals from the regression of fund excess return over previous 36 month and market portfolio excess return, the logarithm of fund total net assets estimated to the end of the previous month, the 1st lag of fund's monthly net cash flow, and expense ratio as at the end of the previous month and defined as the percentage of total investment that shareholders pay for the fund's operating expenses. We also control but do not report coefficients of the monthly normalized cash flow of fund's IOC, turnover ratios as at the end of the previous month and defined as a minimum of aggregate purchases or sales of securities during the year, divided by average fund total net assets, fund age scaled in months, and time-style interaction dummies for each combination of month and style. Panel A (Specification (1)) reports the results for all funds in the sample. Panel B (Specification (2)) reports the results of the regression in which we interact each of the explanatory variables once with a dummy identifying retail funds and once more time with the dummy identifying institutional funds. We also include the dummy identifying institutional funds as a separate variable. The columns titled "Difference Institutional vs. Retail" reports differences between the coefficients of institutional and retail funds from the regression analysis summarized in Panel B, exhibiting the difference in effect of respective variable on fund money flows of the two types of funds. The t-statistics are reported in parentheses. The standard errors are clustered by funds.

	Panel A	Panel B		
	(1)	(2)		
	All Funds	Retail Funds	Intuitional Funds	Difference Institutional vs. Retail
Intercept/ Institutional Dummy Coef.	3.633	3.558	1.021	1.021
	(23.59)	(20.80)	(3.14)	(3.14)
Lagged Monthly Best Performers	0.166	(0.181	0.125	-0.056
	(5.85)	(6.13)	(2.03)	(-0.84)
Lagged Monthly Return	0.063	0.070	0.046	-0.024
	(7.92)	(8.73)	(4.74)	(-3.46)
UMD Loading	1.571	1.442	2.092	0.650
	(8.82)	(7.48)	(5.95)	(1.70)
Jensen's Alpha	2.597	2.465	2.905	0.439
	(38.27)	(33.39)	(22.35)	(3.09)
Tracking Error	-0.297	-0.212	-0.586	-0.374
	(-9.43)	(-6.56)	(-9.45)	(-5.82)
Lagged Monthly Net Cash Flow	0.019	0.017	0.022	0.005
	(17.43)	(14.44)	(9.81)	(1.92)
Expense Ratio	-0.994	-1.098	-0.475	0.623
	(-20.11)	(-19.11)	(-2.86)	(3.56)
R sq. adjusted	0.048	0.050		
No. Fund-Months/Entities	394,361	394,361		
No. Fund- Entities	7,994	7,994		

Control variables included in each regression: Lagged fund size and turnover ratio, fund age, normalized cash flow of fund's IOC, month and style (growth, value, core) interaction dummies

Table 4.3
The Effect of Relative Fund Performance with respect to its IOC

The table reports the coefficients from pooled time-series cross-sectional OLS regressions of funds' monthly normalized cash flow on "Fund Outperforming IOC" dummy variable taking value 1 if a prior month fund return was higher than the average return of all funds of fund's IOC, interaction of prior month fund excess return (defined as a difference between fund return and market return) with "Fund Outperforming IOC" dummy, interaction of prior month fund excess return with [1-"Fund Outperforming IOC"], interaction of fund's Jensen's alpha (calculated over the previous 36 months of fund return) "Fund Outperforming IOC" dummy, interaction of fund's Jensen's alpha with [1-"Fund Outperforming IOC"], interaction of fund tracking error (which is the standard deviation of the residuals from the regression of fund excess return over previous 36 month and market portfolio excess return) with "Fund Outperforming IOC" dummy, interaction of fund tracking error with [1-"Fund Outperforming IOC"]. We also include as control variables but do not report the logarithm of fund total net assets estimated to the end of the previous month, the 1st lag of fund's monthly net cash flow, the monthly normalized cash flow of fund's IOC, turnover and expense ratios as at the end of the previous month, where turnover ratio is a minimum of aggregate purchases or sales of securities during the year, divided by average fund total net assets, and expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. In addition, we include time-style interaction dummies for each combination of month and style. Panel A (Specification (1)) reports the results of the regression analysis conducted for the sample of retail funds. Panel B (Specification (2)) reports the results of the regression analysis conducted for the sample of institutional funds. The t-statistics are reported in parentheses. The standard errors are clustered by funds.

	Panel A: Retail Funds		Panel B: Institutional Funds	
	(1)		(2)	
	Above IOC	Below IOC	Above IOC	Below IOC
Intercept	1.442	____	3.829	____
	(9.15)		(11.25)	
Fund Outperforming its IOC	0.351	____	0.003	____
	(4.49)		(0.02)	
Monthly Excess Return (on IOC)	0.225	-0.047	0.179	0.011
	(8.60)	(-1.77)	(3.58)	(0.25)
Jensen's Alpha	2.690	2.134	3.193	2.982
	(27.15)	(20.10)	(18.96)	(20.64)
Tracking Error	-0.329	-0.326	-0.472	-0.524
	(-8.00)	(-7.66)	(-6.05)	(-7.06)
R sq. adjusted	0.049		0.031	
No. Fund-Months	308,797		114,432	
No. Fund- Entities	5,879		2,524	
Control variables included in each regression:	Lagged fund size, net cash flow, turnover ratio, and expense ratios, fund age, normalized cash flow of fund's IOC, month and style (growth, value, core) interaction dummies			

Table 4.4

The Form of Flow-performance Relationship: Retail versus Institutional Funds

The table reports the coefficients from piecewise pooled time-series cross-sectional OLS regressions of funds' monthly normalized cash flow on fund fractional performance measured with respect to fund IOC (first quintile reflects the lowest 20th performance percentile, fifth quintile – the highest). We also include as control variables but do not report the logarithm of fund total net assets estimated to the end of the previous month, the 1st lag of fund's monthly net cash flow, the monthly normalized cash flow of fund's IOC, in addition, regressions with monthly and annual return includes standard deviation of fund return over the previous 12 months. Panel A reports the results for the performance measures based on fund raw returns estimated at monthly and annual frequency; Panel B reports the results for the performance measures based on fund risk-adjusted returns: Jensen's alpha and fund Fama-French alpha, where fund's Jensen's alpha and fund Fama-French alpha are calculated over the previous 36 months of fund return. In addition, we include time-style interaction dummies for each combination of month and style. The first column of Panel A and Panel B reports the results for all funds in the sample. The last two columns of Panel A and Panel B report the results of the regression in which we interact each of the explanatory variables once with a dummy identifying retail funds and once more time with the dummy identifying institutional funds. The t-statistics are reported in parentheses. The standard errors are clustered by funds.

Panel A

	(1)	(2)	
	All Funds	Retail Funds	Intuitional Funds
Based on Monthly Return			
Bottom Performance Quintile (Monthly)	0.023	0.028	0.006
	(5.34)	(5.73)	(0.63)
2nd Performance Quartile (Monthly)	0.004	0.001	0.010
	(1.49)	(0.52)	(1.63)
3rd Performance Quartile (Monthly)	0.011	0.014	0.003
	(4.45)	(5.51)	(0.60)
4th Performance Quartile (Monthly)	0.011	0.009	0.016
	(3.00)	(2.36)	(1.96)
Top Performance Quintile (Monthly)	0.023	0.026	0.014
	(6.89)	(7.47)	(1.87)
R sq. adjusted	0.035	0.037	
No. Fund-Months	632,036	632,036	
No. Fund- Entities	10,687	10,687	
Based on Annual Return			
Bottom Performance Quintile (Annual)	0.059	0.066	0.035
	(12.39)	(12.95)	(3.26)
2nd Performance Quartile (Annual)	0.028	0.024	0.038
	(10.26)	(8.46)	(5.73)
3rd Performance Quartile (Annual)	0.033	0.034	0.031
	(13.12)	(12.70)	(5.41)
4th Performance Quartile (Annual)	0.026	0.024	0.028
	(6.79)	(6.13)	(3.44)
Top Performance Quintile (Annual)	0.062	0.069	0.047
	(17.03)	(17.30)	(6.11)
R sq. adjusted	0.051	0.052	
No. Fund-Months	632,036	632,036	
No. Fund- Entities	10,687	10,687	
Control variables included in each regression:	Lagged fund size, net cash flow, turnover ratio, and expense ratios, fund age, normalized cash flow of fund's IOC, month and style (growth, value, core) interaction dummies		

Panel B

	(1)	(2)	
	All Funds	Retail Funds	Intuitional Funds
Based on Jensen's Alpha			
Bottom Jensen's Alpha Quintile	0.051	0.054	0.049
	(9.68)	(9.85)	(3.90)
2nd Performance Quartile (Annual)	0.029	0.019	0.057
	(9.33)	(6.01)	(7.43)
3rd Performance Quartile (Annual)	0.029	0.029	0.025
	(10.24)	(10.30)	(3.65)
4th Performance Quartile (Annual)	0.031	0.028	0.039
	(7.39)	(6.51)	(4.05)
Top Jensen's Alpha Quintile	0.049	0.052	0.040
	(12.34)	(12.30)	(4.54)
R sq. adjusted	0.051	0.052	
No. Fund-Months/Entities	413,130	413,130	
No. Fund- Entities	8,208	8,208	
Based on Fama-French Alpha			
Bottom Fama-French Alpha Quintile	0.056	0.054	0.065
	(10.35)	(9.65)	(4.92)
2nd Performance Quartile (Annual)	0.022	0.020	0.032
	(7.12)	(6.39)	(3.92)
3rd Performance Quartile (Annual)	0.027	0.023	0.034
	(9.09)	(7.79)	(4.81)
4th Performance Quartile (Annual)	0.028	0.026	0.032
	(6.92)	(6.39)	(3.36)
Top Fama-French Alpha Quintile	0.044	0.044	0.044
	(11.24)	(10.68)	(4.97)
R sq. adjusted	0.047	0.048	
No. Fund-Months/Entities	413,130	413,130	
No. Fund- Entities	8,208	8,208	
Control variables included in each regression:	Lagged fund size, net cash flow, turnover ratio, and expense ratios, fund age, normalized cash flow of fund's IOC, month and style (growth, value, core) interaction dummies		

Table 4.5
Determinants of Normalized Cash Flows: Expansions versus Recessions

The table reports the coefficients from pooled time-series cross-sectional OLS regressions of funds' monthly normalized cash flow on the 1st lag of best performer dummy getting value 1 if fund monthly return is higher than return of its style in corresponding month and zero otherwise, the 1st lag of fund's monthly return, the momentum (UMD) loading calculated over the previous 36 month of fund return, fund's Jensen's alpha calculated over the previous 36 months of fund return, fund tracking error which is the standard deviation of the residuals from the regression of fund excess return over previous 36 month and market portfolio excess return, the 1st lag of fund's monthly net cash flow, and expense ratio as at the end of the previous month defined as the percentage of total investment that shareholders pay for the fund's operating expenses. We also control but do not report coefficients of the logarithm of fund total net assets estimated to the end of the previous month, the monthly normalized cash flow of fund's IOC, turnover ratios as of the end of the previous month defined as a minimum of aggregate purchases or sales of securities during the year, divided by average fund total net assets, and time-style interaction dummies for each combination of month and style. Panel A reports the results for expansion months. Panel B reports the results for recession months. Panel B reports the results of the regression in which we interact each of the explanatory variables once with a dummy identifying retail funds and once more time with the dummy identifying institutional funds. Specifications (1) and (2) of Panel A and Panel B correspondingly report the results of the regression in which we interact each of the explanatory variables once with a dummy identifying retail funds and once more time with the dummy identifying institutional funds. The columns titled "Difference Institutional vs. Retail" reports differences between the coefficients of institutional and retail funds from the regression analysis summarized in the first two columns of each of the panels, exhibiting the difference in effect of respective variable on fund money flows of the two types of funds. The t-statistics are reported in parentheses. The standard errors are clustered by funds. Level of statistical significance for difference between corresponding coefficients of each type of fund esrimated for expansion and recession months is reported only for the coefficients for which the difference is significant on at most 10% level. A letter **a** denotes 1% significance level, **b** – 5% level, and **c** – 10% level.

%

	Panel A: Expansion Period			Panel B: Recession Period		
	(1)			(2)		
	Retail	Institutional	Difference Institutional vs. Retail	Retail	Institutional	Difference Institutional vs. Retail
Intercept/ Institutional Dummy	3.469 **b**	0.959 **c**	0.959	4.291	0.922	0.922
	(18.14)	(2.51)	(2.51)	(15.24)	(1.93)	(1.93)
Lagged Monthly Best Performers	0.211 **b**	0.128 **c**	-0.083	0.005	-0.124	-0.129
	(6.37)	(1.77)	(-1.08)	(0.08)	(-1.01)	(-0.99)
Lagged Monthly Return	0.090 **a**	0.074	-0.016	0.029	0.024	-0.005
	(8.59)	(5.25)	(-1.68)	(2.36)	(1.66)	(-0.61)
UMD Loading	1.099	2.173 **c**	1.074	0.833	0.313	-0.520
	(4.92)	(5.05)	(2.32)	(2.53)	(0.57)	(-0.86)
Jensen's Alpha	2.263 **a**	2.737 **a**	0.474	4.225	5.404	1.180
	(29.19)	(19.00)	(3.03)	(21.52)	(15.64)	(3.03)
Tracking Error	-0.242 **a**	-0.599 **a**	-0.357	0.185	0.008	-0.177
	(-6.95)	(-8.76)	(-5.09)	(2.50)	(0.06)	(-1.17)
Lagged Monthly Net Cash Flow	0.018 **a**	0.022	0.004	0.012	0.020	0.008
	(14.08)	(8.70)	(1.34)	(8.22)	(8.12)	(2.91)
Expense Ratio	-1.054 **a**	-0.542	0.512	-1.370	-0.344	1.026
	(-16.25)	(-2.70)	(2.44)	(-15.00)	(-1.60)	(4.41)
R sq. adjusted	0.051			0.049		
No. Fund-Months	298,636			94,356		
No. Fund- Entities	6,991			6,149		
Control variables included in each regression:	Lagged fund size and turnover ratio, fund age, normalized cash flow of fund's IOC, month and style (growth, value, core) interaction dummies					

Figure 4.1
Number of Mutual Funds over the period between January 1999 and May 2009

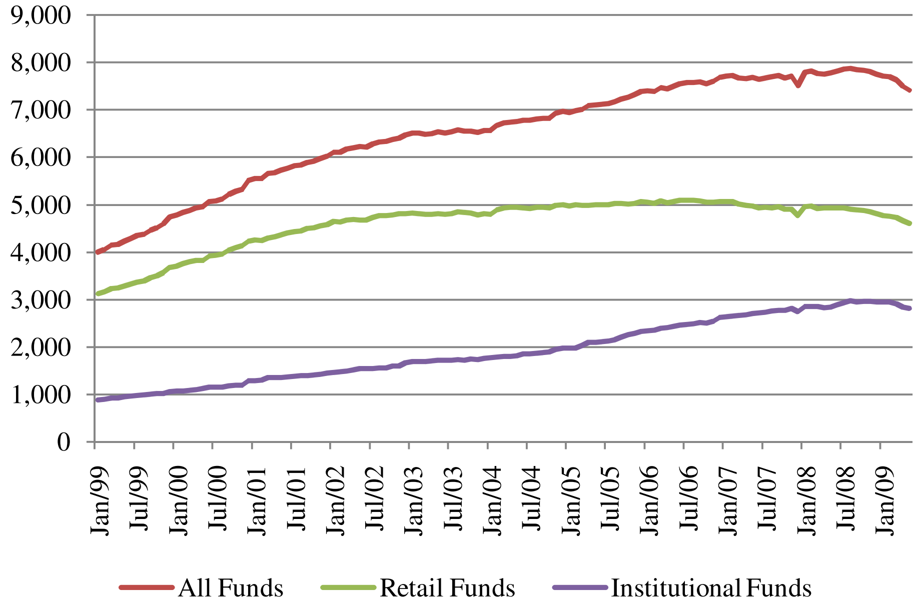


Figure 4.2
Cumulative Monthly Total Net Asset Value (in millions of U.S. dollar) of corresponding group of Mutual Funds over the period between January 1999 and May 2009

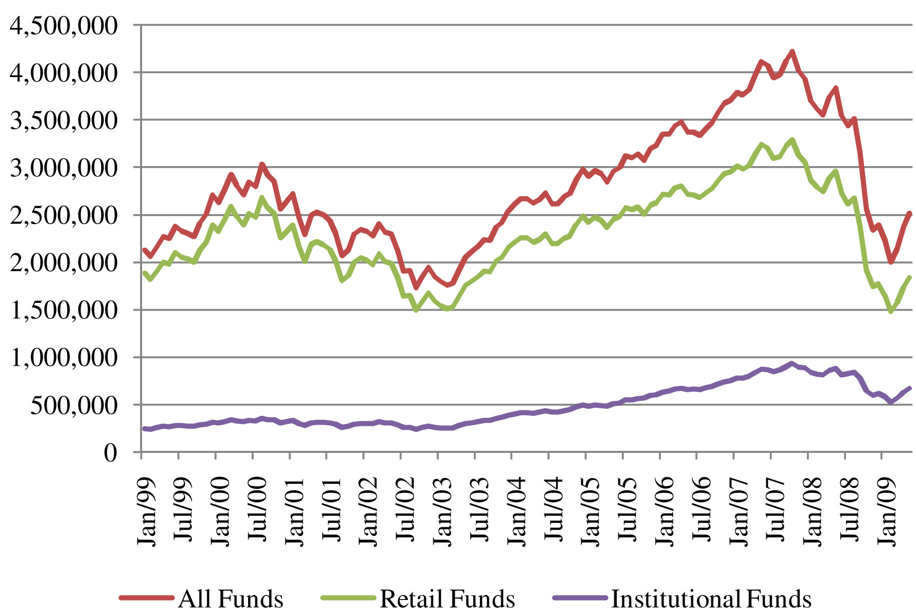
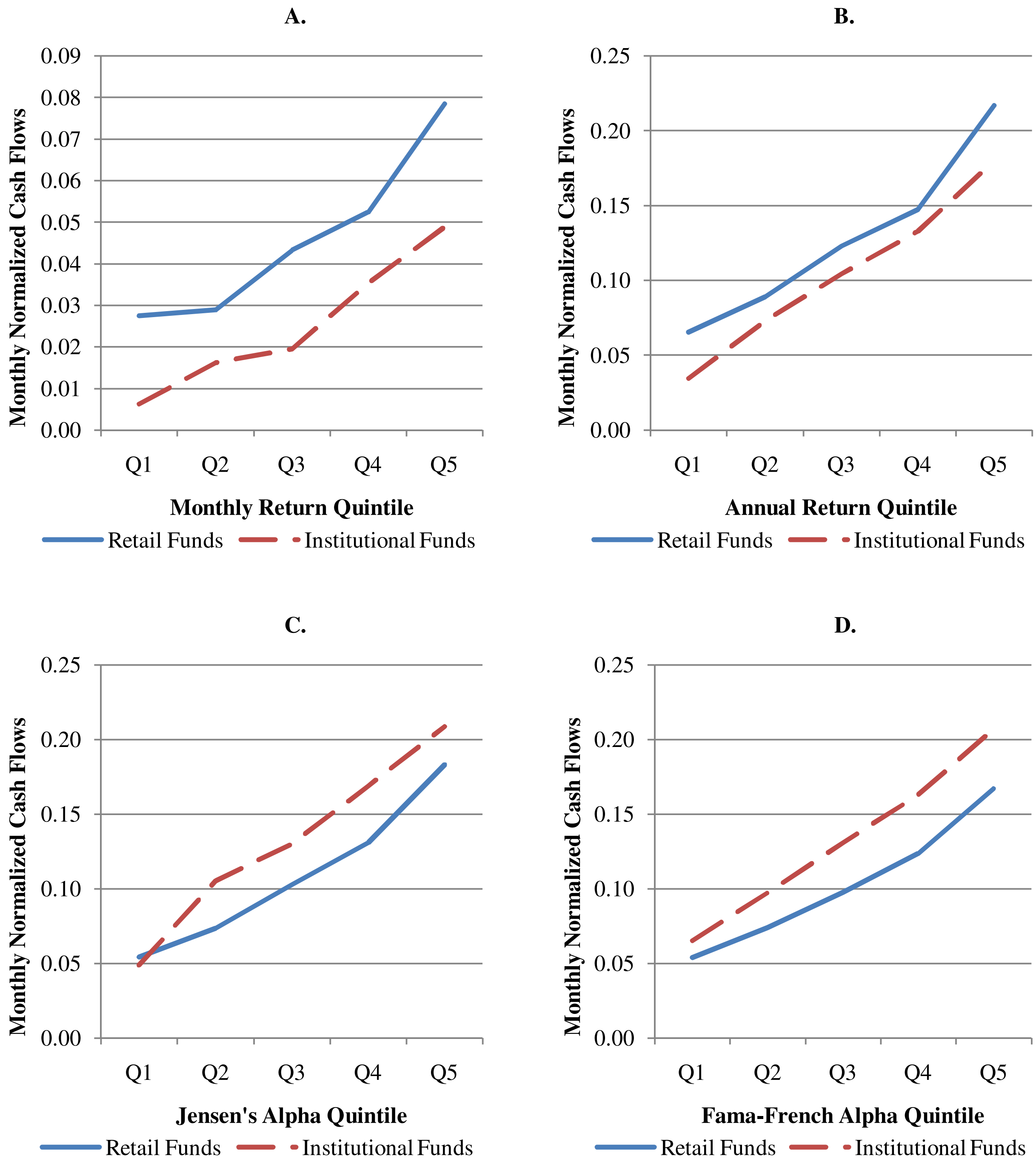


Figure 4.3

The Flow-performance Relationship

The figure summarizes the results reported in Table 4.6 and depicts the relationship between fund monthly normalized cash flows and lagged fractional performance for corresponding performance measures. Graph A shows the relationship for fractional performance measured based on monthly raw return. Graph B shows the relationship for fractional performance measured based on annual raw return. Graph C shows the relationship for fractional performance measured based on fund Jensen's alpha calculated over the previous 36 months of fund return, and graph D shows the relationship for fractional performance measured based on fund Fama-French alpha calculated over the previous 36 months of fund return.



Appendix 4.1

Recession*– Expansion periods over the sample period February 1999 – May 1999 (based on NBER business cycle classification)**

Business Cycle Reference Dates		Duration in Months	
Beginning Date	End Date	Recession	Expansion
February 1999	February 2001		25
March 2001	October 2001	8	
November 2001	November 2007		73
December 2007	May 2009	18	
Total		26	98

*"A recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales." (NBER)

**Source: an official website of the National Bureau of Economic Research (NBER), http://www.nber.org/cycles.html; visited on 07.02.2010.

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