Style Chasing by Hedge Fund Investors

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This draft: November 12, 2008

Abstract

In our paper we examine whether hedge fund money chases investment styles. In line with the style investing theory of Barberis and Shleifer (2003), we find that hedge fund styles indeed compete for investors' money. Better performing and more popular styles are rewarded with higher inflows in the next periods. We explain these results by existence of so-called switchers: investors who compare styles according to style's characteristics relative to other styles, and consequently relocate their funds from styles less successful in the resent past into more successful. Next, we find within style competition of individual hedge funds. Funds out-performing their styles and funds with above style average flows experience higher flows in subsequent periods. We suppose that the reason for within style competition is the investors' search for the best managers. The extremely high level of minimum investments limiting diversification opportunities makes this search particularly important. Finally, we show that hedge funds' version of style chasing represents a smart strategy.

I. 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 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 above a selection among the individual assets. Nowadays, the number of registered hedge funds is far above the level of 10000. Therefore we expect that hedge fund style information has an important impact on the investment decision.

Recent papers investigating investor behavior document evidence for the importance of investment styles (see, e.g. Brown and Goetzmann 2003). 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 allocate money to those styles depending on the relative performance of the styles. An implication of the hypothesis is that within style assets will be equally affected by style competition and therefore co-move. Barberis, Shleifer and Wurgler (2003) test the style investing hypothesis and find that stocks as soon as they are included in an index co-move more than implied by their fundamentals. Pomorski (2004) tests the impact of style level information on mutual fund flows, and reports evidence in conflict with the style investing hypothesis.

A substantial part of the hedge fund literature investigates the flow-performance relation at the individual fund level. Most studies report a positive relation between past performance and money flows into and out of the hedge funds (see, e.g. Agarwal, Daniel and Naik, 2004, Baquero and Verbeek, 2006). However, there is a huge debate going on in these studies about whether this flow-performance relation has a concave, linear or convex shape. 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. However, none of the above studies examines the flow-performance relation at style level. Given the importance of style investing nowadays, this paper will try to fill this gap by examining the effect of information at style level on money flows to a particular style. In case of hedge funds style investing could imply that money flows are positively related with the relative style performance. Although investors may pay attention to individual hedge fund characteristics, information at style level will be of considerable importance. This paper investigates whether hedge fund investors chase well performing hedge fund investment styles. Furthermore, we will examine the effect of style information on the selection of individual funds within a particular style.

Our paper contributes to the hedge fund literature in a number of ways. First of all, the paper empirically tests the style investing hypothesis for the relatively new and dramatically grown asset class of hedge funds. It is interesting and relevant to know whether style investing takes places within this asset class, and what the impact is of style investing on the financial market in general or the hedge fund industry specifically. The inflow of money to the relatively best performing style may have an important price impact for the underlying assets of the investment style. Moreover, 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 the same style. Eventually, this could lead to a diminishing performance of the style in general. Subsequently, the style popularity will disappear and in the worst case the style will stop to exist. This pattern corresponds to what is known as the life-cycle of investment styles.

Second, the paper 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, e.g. , Agarwal, Daniel and Naik (2004); Baquero and Verbeek (2006); Ding, Getmansky, Liang and Wermers (2007); Li, Zhang and Zhao (2007)). However, none of the previous studies examine whether relative style information has an impact on individual fund flows. We will fill this gap by investigating the effect of style characteristics on money flows into and out of hedge funds.

Finally, the paper examines whether style chasing is a smart strategy for investors. Hedge fund investors are usually considered as a more sophisticated investor clientele compared to mutual fund investors. However, hedge fund investors are confronted with liquidity restrictions due to e.g. lock up periods. An investment decision in a hedge fund or hedge fund style can not easily be reversed at a short horizon. This implies that as an investor you have to be more convinced of the appropriatedness and the timing of the investment decision. Therefore it is interesting to examine whether hedge fund investors are behaving in a smart way when they increasingly invest in the most popular strategy of the recent past.

Our main findings are in line with the style investing theory. First of all, we find that the hedge fund industry is characterized by the presence of switchers. In case of hedge funds, these switchers are looking for the best investment strategy via style information. As a result, better performing and more popular styles are rewarded with higher inflows in subsequent periods. Moreover, style popularity positively affects successive money-flows of funds related to this style. Secondly, in contrast to Barberis and Shleifers' style theory, 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 within style competition, a result that is consistent with Getmansky (2005). We suppose that a key factor determining within style competition of funds for investor money is investors' search for the best managers (Li, Zhang and Zhao, 2007, Agarwal, Daniel and Naik, 2008). Apparently, the enormously high level of minimum investments required by an individual hedge fund substantially bounds an option of diversification (see Stulz (2007)), and thereby accelerates 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 pure style chasing does not generate profits implemented as a separate strategy, style chasing is profitable when implemented together with the search for the best within style funds.

The remainder of this paper is organized as follows. In Section II we develop and motivate our hypotheses. In Section III we describe the data and we present some summary statistics of our sample of hedge funds. In Section IV we formally test the hypotheses and we perform a number of robustness checks. Section V tests the effectiveness of implementing a style chasing strategy in the hedge fund industry. Finally, Section VI concludes.

II. Development of Hypothesis

II.A. Related literature

Based on the idea of Mullainathan (2001) that agents employ classifications to make information processing easier, Barberis and Shleifer (2003) introduce the style investing theory. The theory suggests that investors categorize risky assets into styles and allocate funds between these styles depending on the relative performance of those styles. Thereby, style investing implies competition among styles for money flows. Moreover, this competition is based on relative style characteristics rather than absolute. Another implication of the hypothesis is that within style assets are equally affected by style competition and therefore co-move. Simultaneously, this suggestion implies homogeneous distribution of funds within a style.

There are a number of studies testing the style investing hypothesis for different financial sectors. Barberis, Shleifer and Wurgler (2003) assume that index stocks are considered as a separate category, and find 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 within-style return chasing.

At the same time, a number of studies examine the importance of styles. Brown and Goetzmann (1997) and Chan, Chen, and Lakonishok (2002) study the role of investment style in the mutual fund industry. The authors find that style classification is 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 (2003) document that mutual funds related to poorly performing styles tend to change their names. Thereby, these funds on the one hand attempt to get rid off the poor performance image, and on the other hand create an image of winner, getting a name of currently popular styles. The authors also reveal that despite the name change it not necessarily comes together with actual change of fund strategy. Nevertheless, the name change indeed affects subsequent investors' decisions by higher inflows into the fund.

A bunch of recent hedge fund papers discuss the style-performance relation. Agarwal, Daniel and Naik (2000) conduct a so-called generalized style analysis[1] 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 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.

The hedge fund literature suggests a variety of factors determining investment decisions. 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, e.g. , Agarwal, Daniel and Naik (2004); 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 relation between past performance and money flows into and out of the hedge funds (see, e.g. Agarwal, Daniel and Naik, 2004, Baquero and Verbeek, 2006). Using annual time intervals, Agarwal, Daniel and Naik (2004) show that better performance of an individual hedge fund in a given year lead to higher money-flows into this fund in the succeeding year. 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

[1] 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))

that future performance of larger individual hedge funds with greater inflows tends to be worse. Fung, Hsieh, Naik and Ramadoria (2006) 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 in the hedge fund industry fund flows predict future hedge fund performance, while this effect is weaker for funds with share restrictions.

Goetzmann, Ingersoll, and Ross (2003) examine the determinants of money flows into the hedge fund industry. The authors conclude that successful and large fund managers are less willing to receive new investments than small fund managers. Li, Zhang and Zhao (2007) also examine influence of hedge fund manager characteristics on investor behavior. They document that funds with younger managers from higher-SAT undergraduate institutes tend to have higher money flows. Agarwal, Danial and Naik (2008) show important influence of manager compensation scheme, demonstrating that money-flows are positively associated with managerial incentives. The idea behind this finding is that stronger managerial incentives make investors expect better future performance, and thereby attract larger money inflows. However, none of the above studies examines the influence of style on hedge fund money flows.

II.B. Style competition

As it was formulated above, the main idea of our paper is to examine the relevancy and form of style investing for the hedge fund industry. First, we test for the existence of competition among hedge fund investment styles, and thereby examine whether hedge fund investors indeed divide the industry into styles and employ style information when making investment decisions. Intuitively, in the hedge fund industry, investment style 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 a better performance using style information.

The style investing theory suggests that relative rather than absolute style characteristics determine style competition. Barberis and Shleifer explain this pattern by the existence of so-called switchers: investors allocating their funds according to the relative performances of styles. In fact, the existence of switchers is one of the decisive components of style investing. Their activity makes information related to a specific style affect investors' vision of other actually not linked styles. At the same time, this implies that when making investment decision, investors first determine whether the return on a certain style index is higher or lower than that of other styles.

Therefore, to test for the existence of style competition in the hedge fund industry, we use relative style flows and relative style performance. Our first hypothesis is formulated as follows:

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

According to Barberis and Shleifer (2003) the relative past performance of a style creates initial interest in that style, while following after investments attracts even greater investments (money follows money). Trend "money follows money" seems to be especially powerful in the hedge fund industry. Style flows reflect 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 fund's flows predict its future performance.

The key factor for the wide representation of highly professional investors is the type of individual investors symbolizing hedge funds. Except Funds of Funds' investors, the only hedge fund individual investors are so-called high net worth individuals (HNWI), the term that usually is associated with individuals owning more than $1 million in their net worth[2]. Initially, HNW type investors were the main hedge fund investor group[3], looking for a reasonable return on their capital. On the one hand, the extremely high range of average investment requests an adequate level of professionalism in accepting investment decisions. On the other hand, the capital capacities of this investor group allow them to employ the mostly sophisticated advisors. Therefore, the combination of these two factors makes individual investor decisions highly professional.

II.C. Within style competition

Another implication of the style investing theory is that prices of assets grouped in the same style co-move. That implies homogeneous distribution of flows within styles. However, for the hedge fund industry this is not necessarily the case. Since the level of minimal investment required by an individual hedge fund is extremely high, diversification opportunities for investors are very limited (Stulz, 2007). This fact makes the search for the best manager, or alternatively, for the best

[2]For more details about characteristics of hedge fund target investors see Francois-Serge Lhabitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd., page 34.
[3] Appendix 2 illustrates investor composition of hedge fund industry.

qualified managers, highly important for investment decision at within style level. Simultaneously, the search for the best funds within style creates competition for investors' money among funds of the same style. Thereby, the search for the best managers excludes homogeneous investment distribution within a style, as is suggested by the original style investing model.

Indeed, to evaluate hedge fund activity, one has to have an appropriate benchmark. At the same time, style analysis, being 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). Therefore, a hedge fund, evaluated with respect to its benchmark, actually is evaluated with respect to its style. Hence, hedge funds compete among them within styles. Investors do not consider funds of a specific style as identical items in the sense of investment opportunities as it is suggested by the style investing theory. We expect that they do not spread their investments equally among funds of the same style. Consequently, despite that better style characteristics in general attracts higher levels of investment into the style, within fund competition weakens the pure style effect and destructs equality of flows distribution among individual funds of the style. Thereby, our second hypothesis is formulated as follows:

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

II.D. Style classification in hedge fund industry

According to the results of a survey conducted by Alternative investment Management Association in 2003[4], about half (47%) hedge fund industry participants (consultants, investors, and 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.

Unfortunately there is no commonly accepted rule to categorize hedge fund strategies. While hedge fund industry was originally based on a single long-short strategy, nowadays hedge funds use an excess of different investment 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, Harry 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 for

[4] See Francois-Serge Lhabitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd.,.

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. In our study we use the TASS style classification (see Appendix 1 Panel A). This classification is similar to the one suggested by one of the most accepted systems - CS/Tremont[5].

III. Data

III. A. Data Description

Our dataset, provided by TASS, contains information of 2917 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 a basis reported by the fund (monthly, quarterly, or other). Returns are net of all management and incentive fees, but do not reflect front-end and back-end loads (i.e. sales commissions, subscription and redemption fees). Following arguments of Agarwal, Daniel and Naik (2004) and Baquero and Verbeek (2006), we have chosen 1994 as the starting point of our analysis.

From our initial sample we exclude 156 closed-end funds that are present in our database, since subscriptions in 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 a difference in investor composition between FOF and individual hedge funds. While a majority of FOF's 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 these of individual hedge funds might be different 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. On the one hand, most subscription and redemption restrictions are defined on a monthly or quarterly basis. Furthermore, quarterly and monthly horizons seem to be the typical monitoring frequencies among hedge fund investors[6]. Conversely, quarterly horizon has an important advantage on the monthly one. Using quarterly data allows reduction of serial correlation pattern characterizing hedge fund return estimated on monthly basis (Getmansky, Lo and Makarov , 2004).

[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.

[6] In his study about marketing of hedge funds, Beiker (1996) conducted a survey among institutional investors and found that 50% of them prefer to receive quarterly monitoring information about their non traditional investments, around 30% prefer monthly (or between quarterly and monthly) monitoring information, and only 15% monitor less frequently than quarterly.

Since we consider quarterly horizons, we take into account the most recently available value of total net assets (TNA) in each quarter. Furthermore, we restrict attention to funds with a minimum of 5 quarters of return history and with quarterly cash flows available for at least 15 months. While the last selection imposes a survival condition, it ensures that a sufficient number of lagged returns is available to estimate our model and reduce at the same time the effect of a potential instant-history bias[7]. We also exclude observations with extreme rates of net money flows. So, we do not take into account all observations of net flow changes with values higher than 300 percent of change (83 observations are excluded) and lower than 90 percent of change (44 observations are excluded). Our final sample contains 2,274 funds and a total of 33,203 fund-period observations. According to information provided by the database, from 973 graveyard 514 funds are actually liquidated, while the remaining 459 funds are self-selected out of the database for different reasons (e.g. at the fund manager's request or closed to new investment).

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[8]. Hence, the assets under management have grown more than six times over the sample period. Figure 1 displays the trend in assets under management for different styles of the industry. The figure shows that total net assets under management for most of the styles considerably increased over the sample period. At the same time, the plot demonstrates asymmetry in distribution of funds among different styles.

[Figure 1 about here]

We summarize the development of money funds' distribution among the industry styles in Figure 2. As one can infer from the figure, distribution of money funds among styles vary over the sample period. For example, Global Macro, being the largest style at some period, represents one of the smallest styles in the other period. Simultaneously, Figure 2 demonstrates cyclic character of the distribution of money funds. For instance, Managed Futures style decreases its share in the industry over the firs half of the sample period, but strengths its positions over the second half of the period.

[Figure 2 about here]

III.B. Flows Computation

First, we determine flows of style *i* as following:

[7] Instant-history bias (or backfilling bias) has been documented by Park (1995), Ackermann et al. (1999) and Fung and Hsieh (2002), and refers to the possibility that hedge funds participate in a database conditional on having performed well over a number of periods prior to inception.

[8] 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 for 2003 (See Francois-Serge L'Habitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd., plot on the page 21, given by the author respectively from Hedge Fund Research database).

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

where, $Flow_{i,t}$ is the growth rate in total net assets under management of style i over the period between the start and end of quarters t; $TNA_{j,i,t}$ is the total net assets under management of individual 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*.**

We calculate style return as following:

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

where, $R_{j,i,t}$ is the return for fund j related to style i realized during quarter t.

Figure 3 provides an overview of style return over the sample period. There are two patterns that are needed to be stressed. Firstly, one can infer from the figure that there are no permanently winning or loosing styles in terms of performance. For example, in the middle of 1997 Emerging Market style was the best performer and Dedicated Short Bias was the worst, while in the end of 2000 the situation reversed: then Dedicated Short Bias was among leaders while Emerging Market – among losers. Secondly, Figure 3 indicates that a prosperous time for one style might be worsening time for another one. For instance, while at the end of 1999 Emerging Markets style's performance jumped more than 30%, Long/Short Equity Hedge's return dropped by more than 50%.

[Figure 3 about here]

Table 1 provides descriptive statistics for 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, that while this level seems to indicate stability of style flows, the flows appear to be noticeably volatile over time. Over the sample time, each style went through both periods: the period of dramatic outflows and the period of extremely high inflows. For example, Equity Market Neutral style suffering from the harshest level of outflows (-32.66%) lost then almost one third of its assets, while at the other period increased its size by more than one third (36.12%).

[Table 1 about here]

Next, we compute flows for individual funds. To calculate individual fund flows, we use the same technique as for measurement of style flows. In Table 2 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! Clearly, this numbers explain why individual investors representing hedge fund industry are ultimately high net worth individuals.

[Table 2 about here]

All at all, statistics introduced above indicates a few interesting patterns which can be results of competition among hedge fund styles for investor money, or, in other words, results of style investing behavior of hedge fund investors.

IV. Style Chasing

IV. A. Style level investigation

According to the style investing hypothesis (see, Barberis and Shleifer, 2003), investors categorize assets into styles and subsequently allocate money to styles depending on the relative performance of those styles. Further, investors' interest, initiated by relatively high performances of styles, pushes prices of fundamental assets up and thereby attracts additional inflows into the style. Hence, in Barberis and Shleifer's model the key element determining style investing is the interrelation between style flows and prices of style fundamentals. This scheme can not be directly applied to the hedge fund industry, since in hedge funds prices of fundamentals are not observable for investors, and therefore prices and flows do not necessarily affect each other in the way suggested by the original style investing model. However, these facts do not exclude existence of style chasing behavior of hedge funds' investors.

In general, style chasing implies that investors divide potential investment opportunities into styles. Further, they relocate money from past losers into past winner styles, basing their search for the winners on some types of indicators. Finally, in the original model of Barberis and Shleifer, the prices of style fundamentals represent such indicators. We suggest that in line with the style investing model, hedge funds' investors divide funds into styles according to fund's investment strategy as well. Moreover, the hedge fund industry is also characterized by presence of so-called switchers – investors relocating their money from past loser styles into past winners. However, in case of hedge funds, the indicators, used by switchers in their search for winner styles, are different from these suggested by the original style investing model.

Since investors' behavior is reflected in investment decisions, we consider money flows as the main object of our examination of style chasing behavior in the hedge fund industry. We assume that relative style performance and relative style flows represent indicators used by investors in their search for winner styles. Moreover, we claim that relative style flows have a stronger impact on investor decisions. The trend "money follows money" seems to be especially powerful in the hedge fund industry. Style flows reflect believes of investors in the future potential of a specific style. In case of the hedge fund industry investors' beliefs are particularly meaningful, since this industry is characterized by a relatively high concentration of sophisticated investors. This claim is also in line with the finding of Ding, Getmansky, Liang and Wermers (2007) who show that in the hedge fund industry fund's flows predict its future performance.

To measure relative style performance and relative style flows we use simple rankings. At each time point we rank styles in such a way that the best performer takes the highest rank, and the worst – the lowest. Similarly, the rank of style flows reflects the relative level of style flows. So, the style with highest flows takes the highest rank, and the one with the lowest – the lowest. The range of ranks is equal to the number of styles.

Figure 4.a illustrates the relation of relative style flows with relative style flows of previous quarters. The vertical axis is the average rank of style flows at quarter *t-n*. Figure 4.a shows that the higher ranks of style flows are associated with the higher ranks of style flows in the previous quarters, and vise versa. For instance, the style with the lowest level of flows (rank 1) is accompanied by the rank of flows of around 2.5 in the previous quarter. At the same time, the style with the highest rank (10) associated with the rank of style flows of above 7 in the previous quarter. Furthermore, according to the figure, relative style flows seem to have a tendency to change over time gradually rather than sharply. For example, the rank of 1 is associated with the ranks of 2.5, 3, 3.5, and 4 in the previous quarter, half a year, three quarters, and a year respectively. This pattern might imply dependence of relative style flows from past relative style flows.

Figure 4.b shows the relation between relative style flows and relative style performance of previous quarters. Here the link between ranks of previous quarters' style performance and current rank of style flows seems to be much weaker, than in the previously discussed case. Nevertheless, styles with low ranks of flows had slightly lower ranks of previous quarter performance comparing to styles with high ranks of flows. This trend resembles the one for the relation of relative style flows and relative style flows of previous quarters, but it is much weaker. Comparison of relations exhibited in Figures 4.a and 4.b, supports our suggestion that relative style flows play a more important role in investor decisions process than relative style performance.

[Figure 4.a and 4.b about here]

Furthermore, one can expect that, in line with *Hypothesis 1*, that popular and better performing style will stay popular in subsequent periods. Therefore, in the context of our approach to estimation of relative flows, 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, subscription, and redemption periods, we include four lags for ranks of style flow changes, and the same number of lags for these 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. The regression model testing *Hypothesis 1* is:

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

where, $sFlow_{i,t}$ represents flows of style *i* at quarter *t*. $sRnkFlow_{i,t-n}$ is the rank of flows of style *i* at quarter *t-n*. $sRnkR_{i,t-n}$ is the rank of flows of style *i* at quarter *t-n*. $sRisk_{i,t}$ is the risk of style *i* calculated as the standard deviation of the quarterly style return over the four previous quarters. $sSize_{i,t}$ is a control variable for size of the style measured as the natural logarithm of the total net assets under management for style *i* at quarter *t*.

We present the estimation results of Equation 3 in Table 3. The results reveal that 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. So, for instance, an increase of style flows ranking in one point contributes merely 0.8% to the next period style flows. These results suggest that, in line with prediction of our *Hypothesis 1*, popular and better performing styles are granted with higher flows in subsequent periods.

Hence, the results confirm existence of competition among different styles in the hedge fund industry, and thereby support our style chasing claim. As it is also suggested by the original style investing theory of Barberis and Shleifer, we suppose that the main drivers of style competition in hedge fund industry are so-called switchers: investors relocating their money from past winners into future winners. While in the original version of the style investing theory, switchers chase groups of most promising assets, in case of hedge funds, switchers actually look for the best investment strategies. The hedge fund investment strategy is one of the main determinants of its success, while style information is one of the few accessible indicators of a hedge fund strategy. Hence, hedge fund switchers are looking for the best investment strategy via style information.

[Table 3 about here]

In addition, the results show that the impact of style popularity persists for a longer horizon than this of style performance. While style popularity boosts style flows for the next three quarters, the effect of relative style performance holds for merely a quarterly length, and is considerably weaker. More specifically, an additional point in ranking of style return rate contributes around 0.3 percents to the next quarter style flows, which is almost three times lower than the contribution of one point of style popularity ranking (around 0.8%).

To compare the explanatory power of relative style flows and relative style performance, we run separate regressions for each of these variables[9]. Explanatory power of the regression with relative style flows is almost 18 percent, while this of regression with relative style return is only around 5 percent. This difference shows that style popularity has a stronger effect on future style flows than relative style performance.

Summarizing the results of the style level analyses, we find that better performing and more popular styles are rewarded with higher inflows in the next periods. These findings provide support for our claim that in case of hedge funds, investors divide hedge funds into styles according to fund's investment strategy. These results are consistent with the style investing theory of Barberis and Shleifer (2003). Following Barberis and Shleifer argument, we explain these findings by existence of so-called switchers, who in case of hedge funds are looking for the best investment strategy via such style parameters as relative flows and relative performance. Moreover, we show that relative style flows have even a stronger impact on investor decisions.

However, the introduced above analysis does not exclude the situation when investors do not divide funds into styles, but compare funds according to their individual characteristics. In this case, if all the best funds compose the best styles and vise versa the worst funds compose the worst styles, then visual style competition would be just a side effect of fund competition. We respond to this argument in the next section investigating style chasing effect at individual fund level, and show that there is no direct competition among individual funds, but through styles.

IV. B. Individual fund level investigation

In this section we pursue two main purposes. First, to complete the examination started in the previous section, and to show that there is no direct competition among hedge funds, but via styles. Second, to test *Hypothesis 2* and show existence of within style competition implying that within style popular and better performing funds attract higher flows in subsequent periods.

The original style investing theory proposes that once assets are grouped as a style, investors allocate funds at the style level, what, according to the theory, leads to within style prices comovement, implying homogeneous distribution of style flows. The case seems to be different in the hedge fund industry. We argue that investors' money is not distributed equally among funds of a hedge fund style. Since the level of minimal investment required by an individual hedge fund is extremely high, within style diversification opportunities are very limited (Stulz, 2007). This fact makes search for the best fund the key element in the investment decision process at within style level. Simultaneously, search for the best funds within style creates competition for investors'

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

money among funds of the style. This competition no longer allows for homogeneous investment distribution within style, as it suggested by the original style investing model.

At the same time, style parameters serve as a benchmark in evaluation of a hedge fund. Being a main indicator of risk exposures of fund managers, style analysis helps in classifying fund managers and determining an appropriate benchmark for evaluation of their performance (see Agarwal, Daniel and Naik, 2000). Therefore, one can expect within style competition for investors' money, originated by the search for the best funds, to result in higher flows into popular and better performing funds of the style[10]. To examine this claim, we need to construct variables identifying within style popular and within style better performing funds. For this purpose, we define fund with flows exceeding style flows at corresponding time point as popular; funds outperforming their style at corresponding time point are defined as better performing.

To find support for our claim of existence of within style competition and its character, we expect coefficients for within style fund popularity and within style better performing funds to be significant and positive. On the other hand, significant coefficients of both discussed above variables will show that there is no direct competition among hedge funds, but via styles. More specifically, the 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 leaders in its style while another is among losers in its style will have significantly different flows in subsequent periods. Or, that two funds, related to different styles and having all the same characteristics except that one of them is related to a more popular style than the one to which related another fund, will have significantly different flow changes in the next periods. This situation would be impossible under conditions of direct competition of funds.

Direct competition allows for the situation when all the best funds compose the best styles and vise versa the worst funds compose the worst styles. In this case style competition would be just a consequence of fund competition. However, it would also imply the same future flows for funds with all the same characteristics except the style relation. Hence, significant coefficients of variables reflecting fund-style relation would exclude an option that distribution of funds among funds does not depend on the style relation. Consequently, these results would exclude legitimacy of the claim that style competition is only a visual effect, having roots in fund competition. Controlling for other potential determinants of money-flows, we specify the following regression:

[10] Ding, Getmansky, Liang and Wermers (2007) document that hedge fund's flows predict its future performance, and thereby reveal manager qualification as well.

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

where, $fFlow_{j,i,t}$ are the flows of fund *j* related to style *i* at quarter *t*. $fRnkFl_{i,j,t-n}$ is a dummy variable for within style popularity of fund that takes a value one if the fund has above average style flows in the corresponding quarter *t-n*. $fRnkR_{i,j,t-n}$ is a dummy variable for within style winner funds that takes value one if the fund has above average style performance in the corresponding quarter *t-n*. We include control variables for other constant and time varying fund characteristics documented in existing hedge fund literature (see Baquero and Verbeek (2006); Agarwal , Daniel and Naik (2004). $fFlow_{j,i,t-n}$ are the flows of fund *j* related to style *i* at quarter *t-n*. $fR_{j,i,t-n}$ is the return of fund *j* related to style *i* at quarter *t*. $X_{j,i}$ is a vector of characteristics of fund *j* related to style *i* such as risk of fund, size of fund, and other characteristics considered as constant over the sample period. We control also for style characteristics. $sRnkFl_{i,j,t-n}$ is the rank of flows of style *i* at quarter *t-n*. $sRnkR_{i,j,t-n}$ is the rank of performance of style *i* at quarter *t-n*.

Table 4 summarizes the results of the analysis. The results demonstrate that coefficients of all four lags of both – within style popular and better performing funds – are highly significant and positive. This suggests that, in line with our prediction, more popular and better performing funds attract significantly higher flows compared to the less popular and poorly performing ones. Within style popularity seems to have stronger impact on future flows than well-performing. So, flows of a popular fund are expected to be around 7% higher in the next quarter than flows of unpopular one, while flows of a well-performing fund will be granted with an additional 3.5% compared to a bad-performing one. In addition, the results report that the effect of within style popularity and well-performing diminishes over time. For the both variables, coefficients of the first lags are more than three times higher than these of the last.

Moreover, significant coefficients of within style popular and better performing funds exclude an option of direct competition among hedge funds, and thereby confirm presence of style competition. Furthermore, the results show that the effect of style competition deteriorates at within style level. While the coefficients of the first three lags of relative style popularity have comparatively weak economic impact on fund flows but are significant and positive, none of coefficients of relative style performance are significant.

[Table 4 about here]

Summing up, the results of this section confirm existence of style competition in hedge fund industry. They also show that investors' money is not distributed equally among funds of a hedge fund style, as predicted by Barberis and Shleifer's theory. There is within style competition for investors' money, originated by the search for the best funds, and resulting in higher flows into popular and better performing funds of the style.

IV. C. Robustness checks

As is mentioned in Section 2 of this paper, statistics on hedge fund industry shows that the majority of participants of hedge fund industry do use style classifications. However, there is no commonly accepted rule to categorize hedge funds strategies. In our paper, we use style classification provided by TASS to perform the main analysis (see Appendix 1 Panel A). This classification is just the same as the one of the most accepted systems - CS/Tremont.

Hence, to capture the fact that the style classification employed in this study is not the only one commonly used in the hedge fund sector, we redo all steps of our analysis applying the style classification suggested by Agrawal, Daniel and Naik in their paper from 2004 year. The authors use an extensive database provided by different vendors each of which uses his favorite style classification. To define a common classification to their dataset these authors follow the approach of studies of Fung and Hsieh (1997) and of Brown and Goetzmann (2003), demonstrating that hedge fund returns include distinct style factors. Thereby, the authors reclassify all funds in their database into four categories (See Appendix 1 Panel B). This broad classification might serve as a decent common denominator for style classifications used by main information services providers.

Since the classification used by Agarwal, Daniel and Naik (2004) covers not only classification used by TASS but classifications of a few other main vendors, we expect that effect of AND styles on investor decisions will be even stronger than this of TASS classification. Appendix 3 reports the results of analysis based on AND classification. As one can infer, these results stay in line with our prediction. All the style related coefficients at both style and individual fund levels are slightly higher than corresponding coefficients of the analyses based on the TASS classification. Most importantly, these results provide strong support for findings of our main analysis: considerable effect of style on investment decisions in hedge fund industry.

V. Is style chasing indeed justified?

Summarizing findings of our paper, one can see that hedge funds investors chase investing styles. More specifically, styles being more popular tend to keep relatively high flow change rates in the subsequent period. This result comes in line with the hypothesis of style investing theory of

Barbaries and Shleifer (2003) suggesting that a considerable part of investors is looking for future winning styles via today styles' popularity ratings, switching their investments from today losers into winners.

Our results also indicate existence of within style competition of individual hedge funds for money inflows. In other words, flows into a specific style are not distributed equally among hedge funds of this style. Funds being within style winners, in terms of performance and flow changes, tend to have higher inflows in subsequent periods. We explain these results 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 group of funds with potentially successful investment strategies. At the same time, individual characteristics of funds help to find funds that are able to apply the strategy in the best way. It has to be mentioned that style characteristics serve as a benchmark in evaluation of individual fund quality.

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

$$\begin{aligned} fR_{j,i,t} = \beta_0 &+ \sum_{n=1}^{4}\beta_{1,n}\left(fRnkFl_{j,i,t-n}\right) + \sum_{n=1}^{4}\beta_{2,n}\left(fRnkR_{j,i,t-n}\right) + \sum_{n=1}^{4}\beta_{3,n}\left(fFl_{j,i,t-n}\right) + \\ &+ \sum_{n=1}^{4}\beta_{4,n}\left(fR_{j,i,t-n}\right) + \gamma' X_{j,i} + \sum_{n=1}^{4}\beta_{5,n}\left(sRnkFl_{i,j,t-n}\right) + \sum_{n=1}^{4}\beta_{6,n}\left(sRnkR_{i,j,t-n}\right) + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where, $fR_{j,i,t}$ is a return for fund *j* related to style *i* at quarter *t*. $fRnkFl_{i,j,t-n}$ is a dummy variable for within style popularity of a fund that takes a value one if the fund has above average style flows at the corresponding quarter *t-n*. $fRnkR_{i,j,t-n}$ is a dummy variable for within style winner funds that takes value one if the fund has above average style performance at the corresponding quarter *t-n*. We control for individual fund characteristics as past flows and past performance, risk and size. Hence, $fFl_{j,i,t-n}$ are the flows of fund *j* related to style *i* at quarter *t-n*. $fR_{j,i,t-n}$ is the return for fund *j* related to style *i* at quarter *t*. We also control for relative style characteristics. $X_{j,i}$ is a vector of fund characteristics such as risk and size. $sRnkFl_{i,j,t-n}$ is the rank of flows of style *i* at quarter *t-n*. $sRnkR_{i,j,t-n}$ is the rank of performance of style *i* at quarter *t-n*.

Thereby, we test whether better performing and more popular within style funds indeed tend to produce higher performance in the subsequent quarters. We assume that relative fund flows and relative fund performance measured with respect to these of style reflect the idea of hedge fund style chasing behavior. Relevancy of relative fund flows and relative fund performance implies that investors take into account style relation, and hence that styles compete among them for investor money. Simultaneously, it expresses investors' search for the best funds within style, and therefore competition of funds within styles. So, to find a justification for the hedge fund version of style chasing, we expect coefficients of within style popularity and within style best performing to be significant and positive at relevant time horizon.

We report the estimation results of regression 5 in Table 5. The results of the regression analysis show that the coefficient of the second, third and fourth lags of the best within style performers are significant and positive. These findings suggest that, in line with our prediction, funds out performing their style tend to perform better in the next periods. The effect of relative performance of the past half a year appears to be the strongest. So, a fund, out performing its style, in the next half a year is expected to have return on 1.13% higher than a fund underperforming its style. It has to be mentioned, that past half a year relative performance has the strongest impact on fund flows as well. This fact supports the smartness of hedge fund investors' behavior.

Furthermore, the regression results exhibit that the coefficient of the first lag of within style popularity is highly significant and positive. This suggests that within style popular funds show significantly better performance in the next quarter. So controlling for the rest of relevant fund and style characteristics, just due to the fact that one fund is popular within its style and another one is not, the popular one tends to perform at 0.59% better than the later.

The effect of longer lags of fund within popularity is less clear. Their coefficients are merely twice lower than the first lag coefficient, and one of them is negative. However, as previous results in this work show, investors take within style fund popularity into consideration mostly at half year horizon (see Table 4), which makes the third and forth lags of within style popularity irrelevant.

[Table 5 about here]

Summarizing results exhibited in this section, we conclude that, in line with our prediction, in hedge fund industry style chasing implemented together with search for the best within style funds might generate profits.

VI. Conclusions

In our paper we examine whether hedge fund investors chase investment styles, as predicted by style investing theory of Barbaris and Sleifer (2003). We focus on style effect on investment decisions.

In line with style investing theory, we find that hedge fund styles compete for investors' money. We explain this result by present of so-called switchers, investors looking for the future best performing stiles and relocating funds from previously successful styles into future winners. We suggest that in case of hedge funds, switchers are looking for the best investment strategy via such style parameters as relative flows of style and relative performance of style. As a result, better performing and more popular styles are rewarded with higher inflows in the next periods.

Further, 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 of investments into the style, within fund competition weakens style effect. Thereby, better performing and more popular funds within style experience higher inflows in the next periods. We explain this result by within style competition, stimulated by investors search for the best funds. Indeed, to evaluate hedge fund activity, one has to have an appropriate benchmark. At the same time, style analysis, being 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). Therefore, hedge fund, evaluated with respect to its benchmark, actually is evaluated with respect to its style. At the same time, lack of diversification opportunities makes search for the best funds be of highest importance for the investment decision at within style level.

Finally, we test whether 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 within style funds is profitable.

All at all, our study has a few valuable contributions. First, this paper tests empirically the style investing hypothesis for the hedge fund industry. Furthermore, it shows the way hedge fund style is taken into consideration in investment decision process. Next, this our paper examines profitability of hedge funs' version of style chasing. Finally, this study provides an additional tool for prediction of money flows at style and fund level.

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Table 1: Flows by styles over the period 1994 1Q till 2003 4Q

Style	Mean	SD	Min.	Max.
Convertible Arbitrage	7.17	19.04	-17.47	110.74
Dedicated Short Bias	5.43	13.98	-19.57	61.06
Emerging Markets	3.05	10.43	-17.70	43.15
Equity Market Neutral	8.50	11.78	-32.66	36.12
Event Driven	4.03	5.20	-8.86	17.03
Fixed Income Arbitrage	5.20	8.21	-14.89	20.64
Global Macro	-0.93	12.64	-44.57	29.00
Long/Short Equity Hedge	4.53	12.75	-10.39	78.30
Managed Futures	3.30	7.46	-12.71	21.44
Other	0.79	6.54	-19.84	14.46

Table 2: Descriptive statistics of cross-sectional characteristics of individual hedge funds

This table presents summary statistics on some of cross-sectional characteristics of our sample for the period 1994 1Q till 2003 4Q. *Live Funds* is a dummy variable with value one for funds reported as lived at the end of the sample period. *Minimum Investment* is monetary value in million of US $, an investor is requested to allocate into fund. *Management Fee* is a percentage of the fund's net assets under management that is paid annually to managers for administering a fund. *Incentive Fee* is a percentage of profits above a hurdle rate that is given as reward to 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 from her/his 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	SD	Min.	Max.
Live Funds	0.65	0.48	0	1
Minimum Investment	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
ln(TNA of fund)	17.05	1.78	8.11	23.30

Table 3: Style flows and style competition

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

Dependent variable: Style flows

Independent Variable	Estimate		St. Dev
Intercept	3.55		12.748
Rank of Style Flows lag 1	0.81	***	0.254
Rank of Style Flows lag 2	0.50	**	0.201
Rank of Style Flows lag 3	0.63	***	0.195
Rank of Style Flows lag 4	0.03		0.219
Rank of Style Return lag 1	0.32	**	0.158
Rank of Style Return lag 2	0.26		0.162
Rank of Style Return lag 3	-0.08		0.171
Rank of Style Return lag 4	0.06		0.199
Style Risk	-0.31	***	0.081
Style Size	-0.53		0.524
Adjusted R^2	0.18		
Number of observations	400		

Table 4: Fund flows and within style competition of funds

The table reports coefficients of a pooled OLS regression of all funds together; dependent variable: fund flows; independent variables: popular within 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 at corresponding time point 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 - natural logarithm of total net asset value of 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 in millions of US$ dollar; management fees in percents; incentive fees 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 takes the highest rank, and the one with the lowest – the lowest, where range of ranks is equal to the number of styles, 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, the worst – the lowest, when range of ranks is equal to the number of styles, we include four lags of this variable.

Dependent variable: Fund flows

Independent Variable	Estimate		St. Dev
Intercept	13.56	***	1.876
Popular Within Style lag 1 (dummy)	6.69	***	0.306
Popular Within Style lag 2 (dummy)	4.55	***	0.307
Popular Within Style lag 3 (dummy)	2.31	***	0.305
Popular Within Style lag 4 (dummy)	2.18	***	0.300
Winner Within Style lag 1 (dummy)	3.49	***	0.343
Winner Within Style lag 2 (dummy)	3.13	***	0.357
Winner Within Style lag 3 (dummy)	1.60	***	0.324
Winner Within Style lag 4 (dummy)	1.08	***	0.327
Fund Flows lag 1	0.00	***	0.000
Fund Flows lag 2	0.00	***	0.000
Fund Flows lag 3	0.00	**	0.000
Fund Flows lag 4	0.00		0.000
Fund Return lag 1	0.18	***	0.019
Fund Return lag 2	0.12	***	0.018
Fund Return lag 3	0.10	***	0.015
Fund Return lag 4	0.09	***	0.014
Fund Size	-1.74	***	0.095
Fund Risk	-0.26	***	0.021
Live Funds (dummy)	3.26	***	0.304
Minimum Investment	0.00	***	0.084
Management Fee	-0.63	***	0.160
Incentive Fee	-0.01		0.023
High Water Mark (dummy)	2.34	***	0.309
Leveraged (dummy)	0.29		0.292
Personal Capital (dummy)	0.16		0.284
Open to Public (dummy)	0.14		0.428
Dom. Country US (dummy)	-1.52	***	0.288
Rank of Style Flows lag 1	0.55	***	0.048
Rank of Style Flows lag 2	0.41	***	0.046
Rank of Style Flows lag 3	0.10	*	0.046
Rank of Style Flows lag 4	0.019		0.046
Rank of Style Return lag 1	0.08		0.058
Rank of Style Return lag 2	0.07		0.061
Rank of Style Return lag 3	-0.03		0.060
Rank of Style Return lag 4	0.02		0.057
Adjusted R^2	0.11		
Number of observations	33,203		

Table 5: Fund performance and hedge fund version of style chasing

The table reports coefficients of a pooled OLS regression of all funds together; dependent variable: fund return; independent variables: popular within 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 at corresponding time point 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 - natural logarithm of total net asset value of fund at the end of quarter *t*; risk of fund - standard deviation of fund return for four previous quarters; rank of style flows: at each time point we rank styles in such a way that the style with highest flows takes the highest rank, and the one with the lowest – the lowest, where range of ranks is equal to the number of styles, 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, the worst – the lowest, when range of ranks is equal to the number of styles, we include four lags of this variable.

Dependent variable: Fund ROR

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

Figure 1: Total net assets per style over time

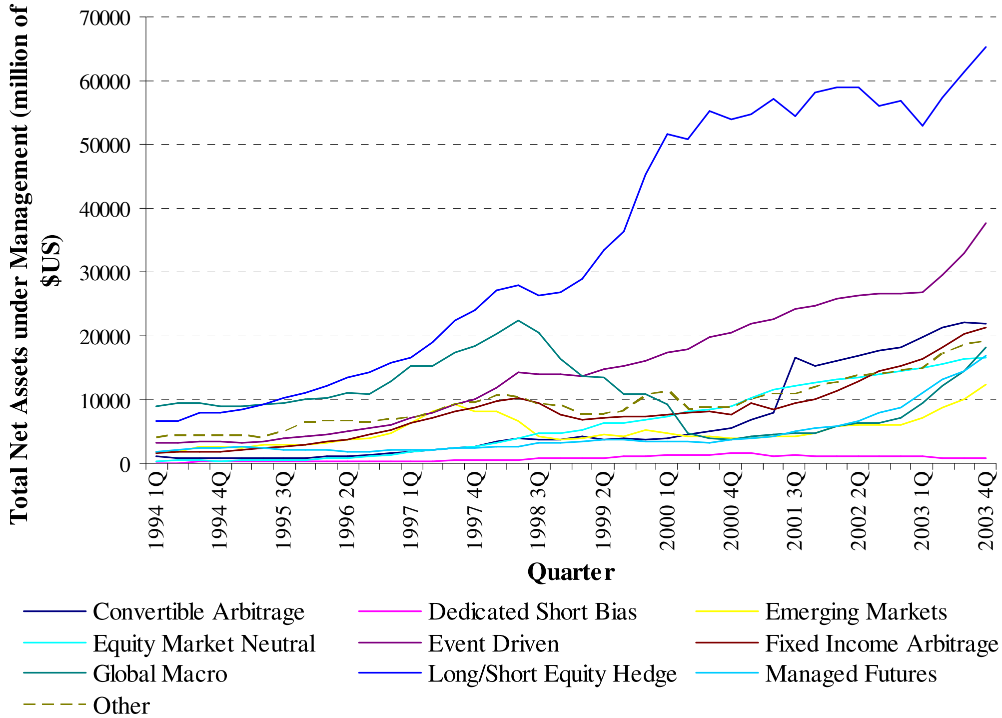


Figure 2: Distribution of money funds among different styles of hedge fund industry over the period 1994 – 2003

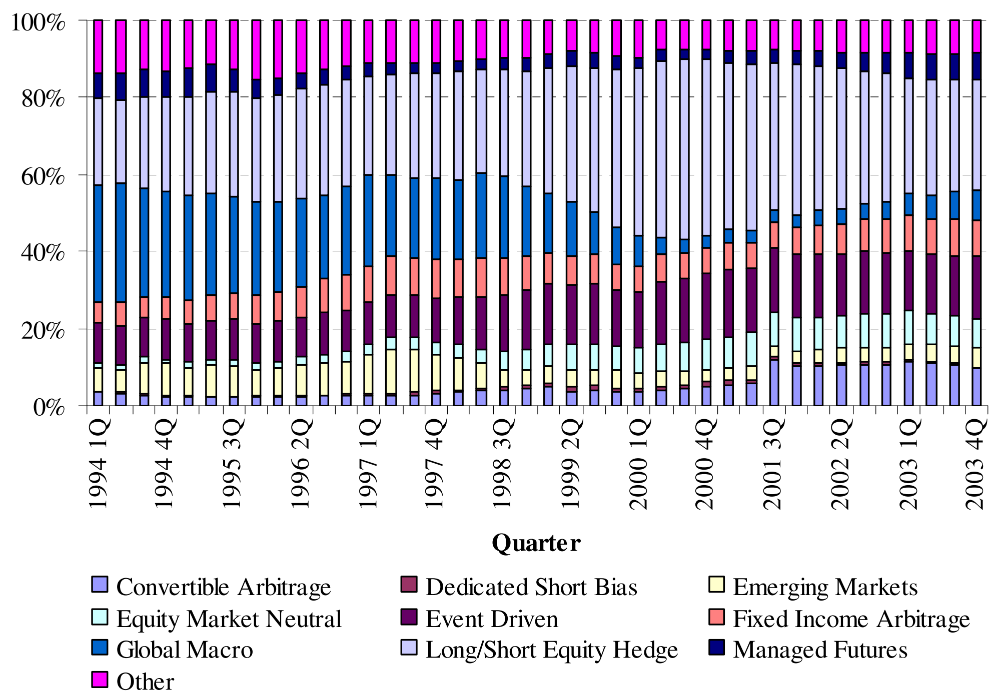


Figure 3: Style returns over time

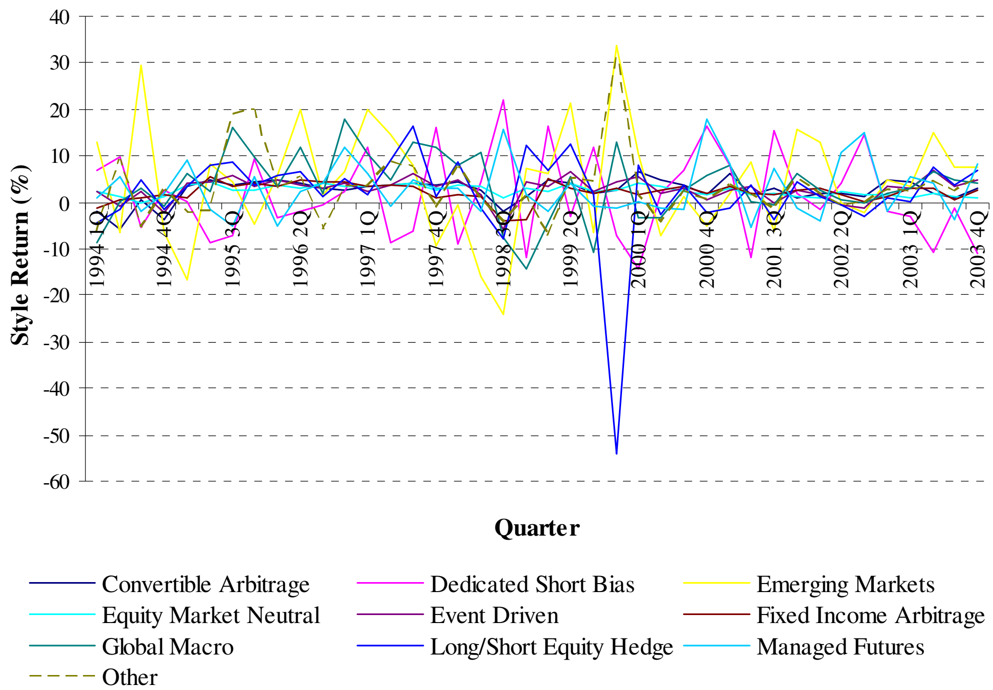


Figure 4.a: Interrelation between present and past style relative flows

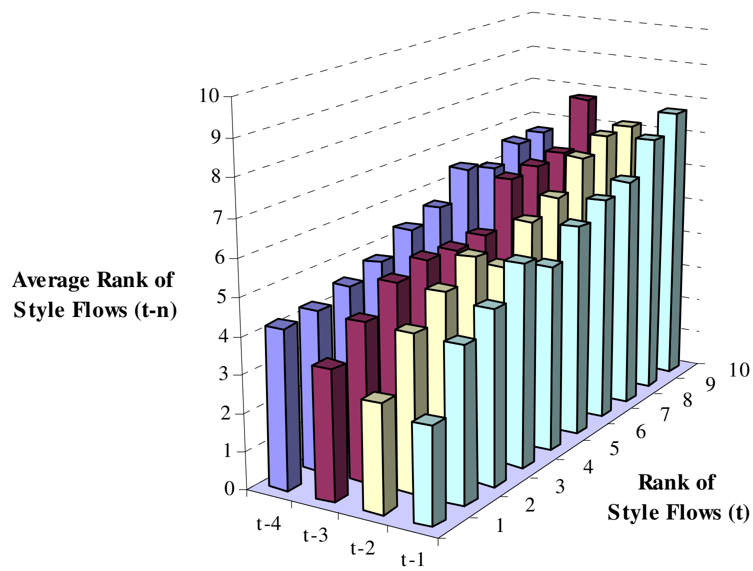
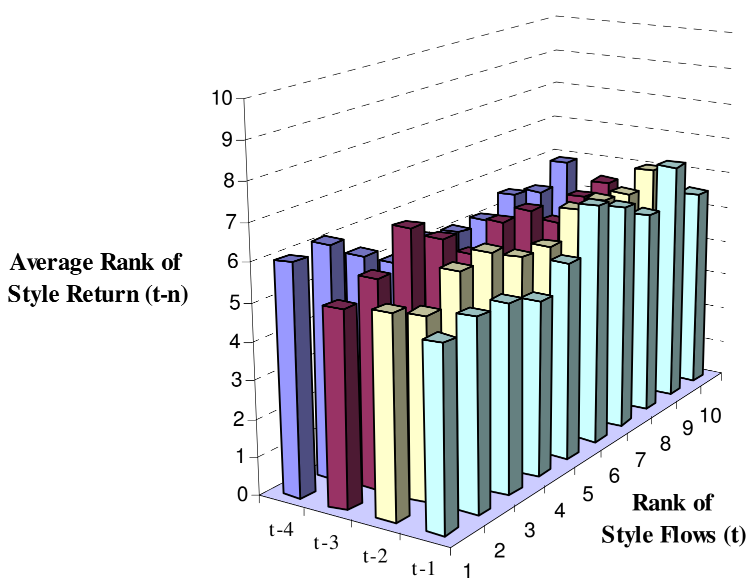


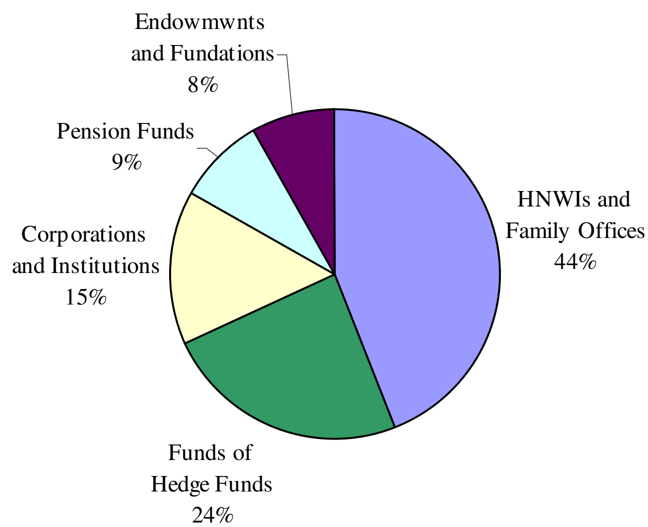
Figure 4.b: Interrelation between present style relative flows and past style relative performances



Appendix 1: Hedge fund style classifications: TASS versus AND[11]

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

Appendix 2: Hedge fund industry investor composition[12]



[11] Style classification according to Agarwal, Daniel and Naik 2004.
[12] From Francois-Serge Lhabitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd., page 35.

Appendix 3: Robustness - AND 2004 style classification

Panel A: Style flows and style competition

The table reports coefficients of pull OLS regression of all styles together; dependent variable: style flows; independent variables: rank of style flows: at each time point we rank style flows in such a way that the style with highest flows takes the highest rank, and the one with the lowest – the lowest, where range of ranks is equal to the number of styles, we include four lags of this variable; rank of style return: at each time point we rank style return in such a way that the best performer takes the highest rank, the worst – the lowest, when range of ranks is equal to the number of styles, we include four lags of this variable; style risk - standard deviation of style return for the four previous quarters; style size – natural logarithm of total net assets under management of style at the end of quarter *t*.

Dependent variable: Style flow

Independent Variable	Estimate		St. Dev
Intercept	-26.44		20.980
Rank of Style Flows lag 1	1.29	***	0.475
Rank of Style Flows lag 2	1.46	***	0.528
Rank of Style Flows lag 3	0.59		0.458
Rank of Style Flows lag 4	-0.34		0.836
Rank of Style Return lag 1	0.20		0.359
Rank of Style Return lag 2	0.65	*	0.370
Rank of Style Return lag 3	0.00		0.360
Rank of Style Return lag 4	0.37		0.388
Style Risk	-0.29	***	0.084
Style Size	0.79		0.827
Adjusted R^2	0.18		
Number of observations	200		

Panel B: Fund flows and within style competition of funds

The table reports coefficients of pull OLS regression of all funds together; dependent variable: fund flows; independent variables: popular within 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 at corresponding time point 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 - natural logarithm of total net asset value of 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 in millions of US$ dollar; management fees in percents; incentive fees 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 takes the highest rank, and the one with the lowest – the lowest, where range of ranks is equal to the number of styles, 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, the worst – the lowest, when range of ranks is equal to the number of styles, we include four lags of this variable.

Dependent variable: Fund flow

Independent Variable	Estimate		St. Dev
Intercept	15.16	***	1.933
Popular Within Style lag 1 (dummy)	6.95	***	0.333
Popular Within Style lag 2 (dummy)	5.20	***	0.324
Popular Within Style lag 3 (dummy)	2.43	***	0.329
Popular Within Style lag 4 (dummy)	2.16	***	0.321
Winner Within Style lag 1 (dummy)	3.74	***	0.360
Winner Within Style lag 2 (dummy)	3.08	***	0.374
Winner Within Style lag 3 (dummy)	1.27	***	0.344
Winner Within Style lag 4 (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 lag 1	0.00	***	0.000
Fund Flows lag 2	0.00	***	0.000
Fund Flows lag 3	0.00	***	0.000
Fund Flows lag 4	0.00		0.000
Fund Return lag 1	0.18	***	0.018
Fund Return lag 2	0.12	***	0.018
Fund Return lag 3	0.11	***	0.015
Fund Return lag 4	0.09	***	0.014
Rank Style Flows lag 1	0.32	**	0.135
Rank Style Flows lag 2	0.60	***	0.149
Rank Style Flows lag 3	0.62	***	0.127
Rank Style Flows lag 4	-0.19		0.135
Rank Style Return lag 1	0.13		0.103
Rank Style Return lag 2	0.30	***	0.105
Rank Style Return lag 3	0.28	**	0.111
Rank Style Return lag 4	0.34	***	0.118
Adjusted R^2	0.11		
Number of observations	33,203		