Style Chasing by Hedge Fund Investors

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Abstract

This paper 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 into more successful hedge fund investment styles of the recent past. Furthermore, we find evidence for within style competition between individual hedge funds. Funds outperforming their styles and funds with above style average inflows experience higher inflows in subsequent periods. One of the reasons for within style competition 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 within-style fund selection represents a smart strategy.

JEL classification: G11, G12, G23

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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 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 above a selection among 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. This paper 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 for the importance of investment styles (see, e.g. 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 current hedge fund literature studies the role of investment style documenting its particular importance and other investigates factors driving investment decisions, there is none that really pays attention to the link between investment style and investment decisions. We fill this gap examining the way hedge fund style is taken into consideration in investment decision process.

Our paper contributes to the hedge fund literature in a number of ways. First of all, the paper empirically tests 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 it 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 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 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. 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 paper we will investigate 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. In 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 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 term. This implies that as an investor you have to be more convinced of the appropriatedness 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 within 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 in a smart way when they increasingly invest in the most popular strategy of the recent past.

Our main findings are as follows. First of all, we find that better performing and more popular styles are rewarded with higher inflows in subsequent periods. Style popularity positively affects successive money-flows of funds related to this style. 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 within style competition, a result that is consistent with Getmansky (2005). 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 the 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 describe the data and we present some summary statistics of our sample of hedge funds. In Section III we develop and motivate our hypotheses, while in Section IV we formally test the hypotheses and perform a number of robustness checks. Section V concludes.

II. Data

Our survivorship free 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. 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. Quarterly data reduces patterns of serial correlation characterizing hedge fund returns on monthly basis (Getmansky, Lo and Makarov, 2004). We take into account the most recently available value of total net assets (TNAs) 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 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 (83 observations are excluded) or lower than -90 percent (44 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[3]. Hence, the assets under management have grown more than six times over the sample period.

In Table 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 make use of leverage, i.e. about 73%, and 55% of the funds register that the fund manager invested personal capital.

[Table 1 about here]

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 style 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 funds. While the hedge fund industry was originally based on a single long-short strategy, nowadays hedge funds use an excess of different investment strategies. In our study we use the TASS style classification that is similar to the one suggested by one of the most accepted systems - CS/Tremont[5]. For robustness checks we also use the classification as suggested by Agarwal, Daniel and Naik (2004). They determine four broad styles

[3] 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).
[4] See Francois-Serge Lhabitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd.,.
[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.

and we refer to this classification as the ADN styles. Alternative classifications exist as well (see, e.g. Okunev and White (2003), Harry and Brorsen (2004)). Table 2 presents the two style classifications, while Figure 1 displays the trend in assets under management for different TASS styles of the industry. The figure shows that total net assets under management for most of the styles considerably increased over the sample period. For instance, the largest over almost the whole sample period style – Long/Short Equity – at the end of year 2003 had about ten time more assets under management than at the beginning of the year 1994, while the most prominent growth is observed for the Equity Market Neutral style that enlarged over the sample period by almost 45 times. At the same time, the difference in the growth rates of hedge fund styles indicates asymmetry in distribution of funds among different styles.

[Figure 1 about here]

We summarize the development of the TNAs' distribution among the industry styles in Figure 2. As one can infer from the figure, the distribution of TNAs among styles varies 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 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.

[Figure 2 about here]

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

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

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:

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

where, $R_{j,i,t}$ is the return of fund j related to style i and realized during quarter t. Figure 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 loosing 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 prosperous time for one style might affect the 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%.

[Figure 3 about here]

Table 3 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, that while this level seems to indicate stability of style flows, the flows appear to be noticeably volatile over time. During our sample period, each style went through both periods: a period of dramatic outflows and a period of extremely high inflows. For example, Equity Market Neutral style had the highest level of outflows (-32.66%) and lost then almost one third of its assets, while in a later period it increased its size by more than one third (36.12%).

[Table 3 about here]

III. Hypotheses and Methodology

In the previous section we have seen indications of patterns in the market shares of hedge fund investment styles. From the hedge fund literature it is well known that at individual fund level past performance and fund characteristics appear to have a significant impact on the money flows to particular funds. Given the importance of style classifications nowadays, we expect that information at style level affects the money flows to a particular hedge fund investment style initially. In a second stage, investors decide which fund to choose within a particular style.

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. Thereby, these funds attempt to get rid off the poor performance image, and try to 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 number of hedge fund papers investigate the style-performance relation. Agarwal, Daniel and Naik (2000) conduct a so-called generalized style analysis[6] to examine 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 (2003) show evidence for 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 important elements in the investment decisions of hedge fund investors.

In this paper 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.

Style investing suggests that relative rather than absolute style characteristics determine competition for investors' money (Barberis and Shleifer, 2003). Moreover, it implies that when making investment decisions, investors first 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

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[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))

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. 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. The range of ranks is equal to the number of styles. The regression model testing *Hypothesis 1* is:

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

where $sFlow_{i,t}$ represents flows of style *i* at quarter *t*. $sRnkFlow_{i,t-n}$ is the rank of 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*. $sRisk_{i,t}$ is the risk of style *i* calculated as the standard deviation of the quarterly style 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 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 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 flows predict its future performance.

At individual fund level 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); 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 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 that 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 in the hedge fund industry fund flows predict future hedge fund performance, while this effect is weaker for funds with share restrictions. However, none of the above studies examines 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 the choice for a particular hedge fund.

In this paper 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 within-style relative flows and relative performance of hedge funds positively affect the inflows into the individual funds.

We specify the following regression equation:

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

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 the 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 winning funds 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 $X_{j,i}$ 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. $sRnkFl_{i,j,t-n}$ 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 line with our second hypothesis, we expect coefficients for within style fund popularity and within style better performing funds to be significant and positive. Significant coefficients of both discussed above variables will show that there is no direct competition among hedge funds, but 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 to examine whether a 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 instrument of closing down a fund for new investors. In this way they can circumvent the treat of having to invest a lot of new money, 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 competition between funds within that style due to an increase in the number of funds offered with the same style. This could lead to a diminishing performance of the style in general as shown by Naik, Ramadorai and Stromqvist (2007). However, this does not necessarily imply that a strategy of investing in the best performing and most popular investment style at a certain moment in combination with within-style fund selection is not a profitable strategy. Our third hypothesis is formulated as follows:

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

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

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

where, $fR_{j,i,t}$ is the return or risk-adjusted 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 of one if the fund has above average style flows in quarter *t-n*. $fRnkR_{i,j,t-n}$ 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 as past flows and past performance, risk and size. $fFl_{j,i,t-n}$ are the flows of fund *j* related to style *i* in quarter *t-n*. $fR_{j,i,t-n}$ is the return or risk-adjusted for fund *j* related to style *i* in quarter *t-n*. We also control for relative style characteristics. $X_{j,i}$ is a vector of fund characteristics such as risk and size, while $sRnkFl_{i,j,t-n}$ 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 *t-n*. In line with hypothesis 3, we test whether better performing and more popular within-style funds tend to produce higher performance in subsequent quarters.

IV. Style Chasing

Our first question of interest is whether relative style performance and relative style popularity affect the money flows of a specific hedge fund investment style. Panel A of Table 4 presents the estimation results of Equation 3 when performance is measured by raw style returns, while Panel B shows the results when performance is measured by risk-adjusted returns. In case of raw style returns, 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 the style flow ranking with one point contributes merely 0.8% to the next period style flows. Furthermore, an increase in the style performance ranking with one point would increase next period style flows with more than 0.3%. These results suggest that, in line with *Hypothesis 1*, that popular and better performing styles are granted 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 merely a quarterly length, and is considerably weaker. It appears that the risk of a hedge fund investment style has a dampening effect on the money flows to a style. In case we measure the performance as a risk-adjusted style return, we find similar results for past style popularity. However, the impact of lagged relative style performance is not significant anymore. 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.

[Table 4 about here]

To compare the explanatory power of relative style flows and relative style performance, we run separate regressions for each of these variables[7]. The explanatory power of the regression with relative style flows is almost 18 percent, while this of a regression with relative style performance is only around 5 percent. This difference shows that style popularity has a stronger effect on future style flows than relative style performance. The results of the style level analyses show that better performing and more popular styles are rewarded with higher inflows in the next periods. These findings support the claim of style chasing in the case of hedge funds. Apparently, investors divide hedge funds into styles according to the fund's investment strategy, and increasingly invest in the relatively 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 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 investigate the style chasing effect at individual fund level, and show that there is no direct competition among individual funds, but through styles. At individual fund level the hedge fund literature suggests a variety of factors determining 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 huge universe of hedge funds, we expect that style information is also an important factor in the choice for a particular hedge fund.

Table 5 summarizes the results of the estimation of Equation 4 in which we test whether within-style relative flows and relative performance of hedge funds positively affect the inflows into the individual funds. Panel A shows the results when performance is measured by raw returns, while Panel B shows the results for risk adjusted returns.

[Table 5 about here]

In the table we consider three sets of variables, within-style, fund specific and general. The results in Panel A demonstrate that the within-style coefficients of all four lags of both – within-style popularity and within-style winner as measured by raw returns– are highly significant and positive.

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

This suggests that, in line with Hypothesis 2, more popular and better performing funds within a style attract significantly higher money flows compared to the less popular and poorly performing ones. Within-style popularity seems to have stronger impact on future flows than performance. So, flows of a popular fund are expected to be around 7% higher in the next quarter than the 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 show that the effect of within-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 last. The estimates for the fund specific variables are in line with the previous literature. Lagged fund returns have a positive impact on the inflows of the funds, while bigger and more risky funds receive less money compared to 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. In case the ranking of the style popularity the fund belongs to would increase with one point, the fund can expect 0.55% additional money flows. However, none of the coefficients of relative style performance are statistically significant. For risk-adjusted returns we find similar results. In line with the analysis at style level, performance measured by risk-adjusted returns has marginal impact on individual fund flows. The significant coefficients for within style popularity and performance are in line with our statement of the absence 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.

So far the results of this section confirm existence of style competition in the hedge fund industry. A considerable part of the hedge fund investors is looking for future winning styles via today's style popularity ratings, switching their investments from past losers into past winners. Furthermore, investors' money is not distributed equally among funds within a hedge fund style. There is within style competition for investors' money, originated by the search for the best funds, and resulting in higher money flows into popular and better performing funds of the style.

Now the question is whether a 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 hedge fund investors. 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 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.

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. However, in contrast to mutual fund managers, individual hedge fund managers have the instrument of closing down the fund for new investors. In this way they can circumvent the treat of having to invest a lot of new money, potentially affecting the funds' performance negatively. However, we expect that the inflow of new money to a particular successful style affects the competition between funds within that style due to an increase in the number of funds offered with the same style. In order to analyze factors affecting the number of funds within a specific style, we have to distinguish between two opposite processes: one is the introduction of new funds, while at the other side existing funds can be liquidated. 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 till the moment they have decent return records. Nevertheless, most hedge funds will most probably continue reporting until they are liquidated. Therefore, we expect that style popularity has a positive effect on survivorship of individual funds within the style, and thereby higher style popularity is expected to be associated with a decrease in the number of liquidated funds within the style.

To test the above suggestions, we perform regression analysis of the following form:

$$sNumbF_{i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n}\left(sRnkFlow_{i,t-n}\right) + \beta_2\left(sRisk_{i,t}\right) + \beta_3\left(sSize_{i,t}\right) + \varepsilon_{i,t} \tag{6}$$

where $sNumbF_{i,t}$ represents the number of funds related to style *i* and reporting at quarter *t* for the first time, in the regression analysis studying an influence of style popularity on the number of new funds within style. It 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 quarterly style 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 6 we present results of the analysis testing influence of style popularity on number of new and liquidated funds within style. In line with our predictions, the effect of style competition for investors' money on the number of newly founded individual 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 line with studies that examine factors affecting survival probabilities (see, e.g. Baquero, Ter Horst and Verbeek (2005)). Table 7 reports the estimation results of Equation 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 indicate that funds outperforming 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, outperforming its style, is expected to have return in the next half a year that is 1.13% higher than a fund underperforming its style. It has to be noted that the 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. This in contrast to Berk and Green's model that predicts diminishing returns to scale. So controlling for fund and style characteristics, it appears that 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 latter. The effect of longer lags of within style 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 show, investors take within style fund popularity into consideration mostly at half year horizon (see Table 4). So, in line with our prediction, in the hedge fund industry style chasing implemented together with search for the best within style funds might be a successful strategy.

[Table 6 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 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.

As is mentioned in Section II of the paper, statistics on hedge fund industry shows that the majority of participants in the hedge fund industry use style classifications. However, there is no commonly accepted rule to categorize hedge funds strategies. In our paper, we use the style classification provided by TASS to perform the main analysis. 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 Agarwal, Daniel and Naik (2004). 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 the 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 Table 2). This broad classification might serve as a decent common denominator for style classifications used by main information services providers.

Appendix 3 reports the results of the analysis based on the ADN style classification. As one can infer, these results are in line with the earlier results. The style related coefficients at both style and 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: a considerable effect of style on investment decisions in the hedge fund industry.

V. Conclusion

In our paper we examine whether hedge fund investors chase investment styles, focusing on the style effect in investment decisions. We find that hedge fund styles compete for investors' money. We explain this result by investors' tendency to look for the future best performing styles and reallocating funds from previously successful styles into future winners. The findings are in line with the style investing theory of Barberis and Shleifer (2003). We suggest that hedge funds investors are looking for the best investment strategy via style parameters such 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.

Furthermore, we find that within style money flows are not equally distributed. Despite that in general style popularity attracts higher investments into the style, within fund competition weakens the style effect. 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. 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)).

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 within style funds is profitable.

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Table 1: 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 2: Hedge fund style classifications: TASS versus AND[8]

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
Multi-Strategic	Other

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

Table 3: 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
Multi-Strategic	0.79	6.54	-19.84	14.46

Table 4: 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: in column A, at each time point, we rank style return in such a way that the style with the highest row return takes the highest rank, with the lowest – the lowest; in column B/C, at each time point we rank alpha of style return, calculated based on three-factor Fama-French model/seven-factor Fung-Hsieh model, in such a way that style with the highest alpha takes the highest rank, with the lowest – 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*.

	(A)			(B)			(C)		
Dependent variable: Style flow	**Model of Raw Returns**			**Model of Risk Adjusted Return based on Fama-French 3-Factors**			**Model of Risk Adjusted Return based on Hsieh-Fung 7-Factors**		
Independent Variable	**Estimate**		**St. Dev**	**Estimate**		**St. Dev**	**Estimate**		**St. Dev**
Intercept	3.55		12.748	-28.90	*	17.105	-31.25	*	16.006
Rank of Style Flows lag 1	0.81	***	0.254	1.14	***	0.336	1.22	***	0.328
Rank of Style Flows lag 2	0.50	**	0.201	0.41	*	0.234	0.42	*	0.225
Rank of Style Flows lag 3	0.63	***	0.195	0.39	*	0.208	0.33	*	0.200
Rank of Style Flows lag 4	0.03		0.219	0.09		0.299	0.10		0.271
Rank of Return/FF Alpha/FH Alpha lag 1	0.32	**	0.158	0.26		0.293	-0.13		0.289
Rank of Return/FF Alpha/FH Alpha lag 2	0.26		0.162	-0.01		0.436	0.21		0.512
Rank of Return/FF Alpha/FH Alpha lag 3	-0.08		0.171	-0.19		0.323	-0.97	*	0.506
Rank of Return/FF Alpha/FH Alpha lag 4	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
Adjusted R^2	0.18			0.17			0.20		
Number of observations	400			250			250		

Table 5: 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 – in column A/B/C dummy getting value 1 if at corresponding time point a fund row return/Fama-French return alpha/Fung-Hsieh return alpha is higher than row 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 A/B/C four lags of fund row return/Fama-French return alpha/Fung-Hsieh return alpha; 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; in column A/B/C rank of style row 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 row return/Fama-French return alpha/Fung-Hsieh return alpha takes the highest rank, with the lowest – the lowest, when range of ranks is equal to the number of styles, we include four lags of this variable.

Dependent variable: Fund flows	(A) Model of Raw Returns			(B) Model of Risk Adjusted Return based on Fama-French 3-Factors			(C) Model of Risk Adjusted Return based on Fung-Hsieh 7-Factors		
Independent Variable	**Estimate**		**St. Dev**	**Estimate**		**St. Dev**	**Estimate**		**St. Dev**
Intercept	13.56	***	1.876	1.02		2.988	0.96		2.879
Popular Within Style lag 1 (dummy)	6.69	***	0.306	5.27	***	0.515	5.40	***	0.514
Popular Within Style lag 2 (dummy)	4.55	***	0.307	4.14	***	0.483	4.21	***	0.481
Popular Within Style lag 3 (dummy)	2.31	***	0.305	2.47	***	0.475	2.51	***	0.480
Popular Within Style lag 4 (dummy)	2.18	***	0.300	1.69	***	0.471	1.80	***	0.474
Winner Within Style lag 1 (dummy)	3.49	***	0.343	1.42	*	0.756	0.31		0.578
Winner Within Style lag 2 (dummy)	3.13	***	0.357	0.03		0.836	0.81		0.718
Winner Within Style lag 3 (dummy)	1.60	***	0.324	0.33		0.730	-0.15		0.650
Winner Within Style lag 4 (dummy)	1.08	***	0.327	-0.80		0.652	-1.29	**	0.564
Fund Flows lag 1	0.00	***	0.000	0.01		0.006	0.01		0.006
Fund Flows lag 2	0.00	***	0.000	0.00		0.001	0.00		0.002
Fund Flows lag 3	0.00	**	0.000	0.00	*	0.001	0.01	*	0.001
Fund Flows lag 4	0.00		0.000	-0.01		0.004	-0.01		0.004
Fund Return/FF Alpha/FH Alpha lag 1	0.18	***	0.019	0.45	***	0.110	-0.02	*	0.009
Fund Return/FF Alpha/FH Alpha lag 2	0.12	***	0.018	-0.17		0.127	-0.00		0.011
Fund Return/FF Alpha/FH Alpha lag 3	0.10	***	0.015	-0.36	***	0.108	-0.01		0.010
Fund Return/FF Alpha/FH Alpha lag 4	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
Rank of Style Flows lag 1	0.55	***	0.048	0.45	***	0.087	0.46	***	0.084
Rank of Style Flows lag 2	0.41	***	0.046	0.44	***	0.093	0.44	***	0.092
Rank of Style Flows lag 3	0.10	*	0.046	0.10		0.098	0.12		0.099
Rank of Style Flows lag 4	0.019		0.046	0.14		0.097	0.11		0.094
Rank of Return/FF Alpha/FH Alpha lag 1	0.08		0.058	-0.12		0.115	-0.01		0.081
Rank of Return/FF Alpha/FH Alpha lag 2	0.07		0.061	-0.05		0.117	0.01		0.099
Rank of Return/FF Alpha/FH Alpha lag 3	-0.03		0.060	0.38	***	0.114	0.15		0.108
Rank of Return/FF Alpha/FH Alpha lag 4	0.02		0.057	-0.25	**	0.108	-0.28	***	0.087
Adjusted R^2	0.11			0.06			0.06		
Number of observations	33,203			9,898			9,898		

Table 6: The Effect of Style Popularity on Number of New/Liquidated Funds within Style

Panel A:

The table reports coefficients of pooled OLS regression of all styles together; dependent variable: number of new funds within style; 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; 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: number of new funds

Independent Variable	Estimate		St. Dev
Intercept	-73.195	***	8.605
Rank of Style Flows lag 1	-0.004		0.129
Rank of Style Flows lag 2	0.175		0.124
Rank of Style Flows lag 3	0.116		0.115
Rank of Style Flows lag 4	0.016		0.123
Style Risk	0.343	***	0.110
Style Size	3.393	***	0.369
Adjusted R^2	0.305		
Number of observations	400		

Panel B:

The table reports coefficients of pooled OLS regression of all styles together; dependent variable: number of liquidated funds within style; 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; 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: number of dead funds

Independent Variable	Estimate		St. Dev
Intercept	-35.856	***	5.467
Rank of Style Flows lag 1	-0.165	**	0.081
Rank of Style Flows lag 2	-0.064		0.086
Rank of Style Flows lag 3	-0.056		0.079
Rank of Style Flows lag 4	0.020		0.081
Style Risk	0.136	***	0.049
Style Size	1.773	***	0.252
Adjusted R^2	0.238		
Number of observations	400		

Table 7: 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

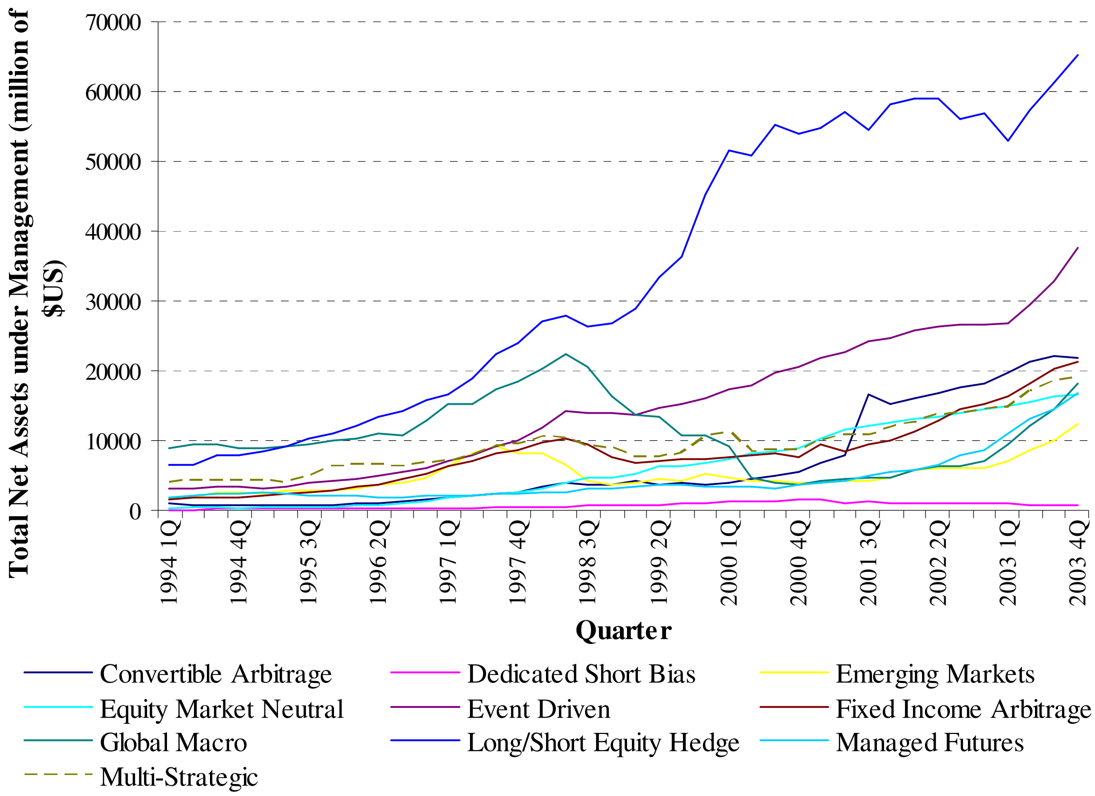


Figure 2: Distribution of money funds among different styles of hedge fund industry over the period 1994 – 2003

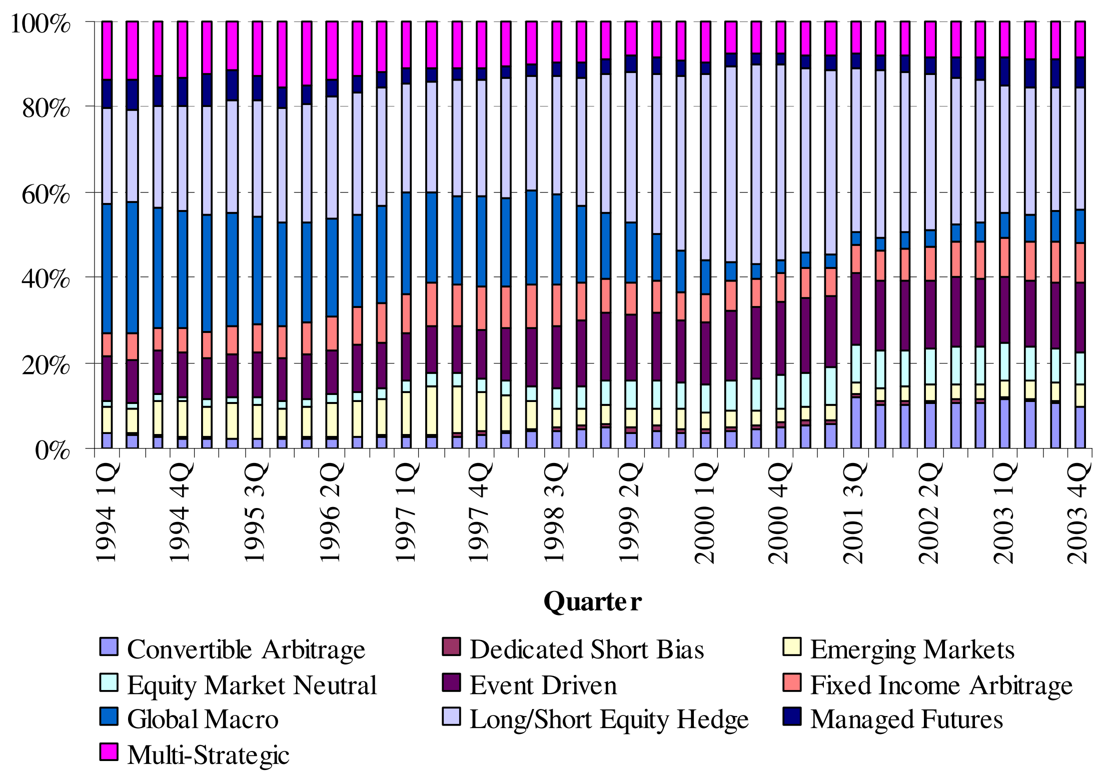
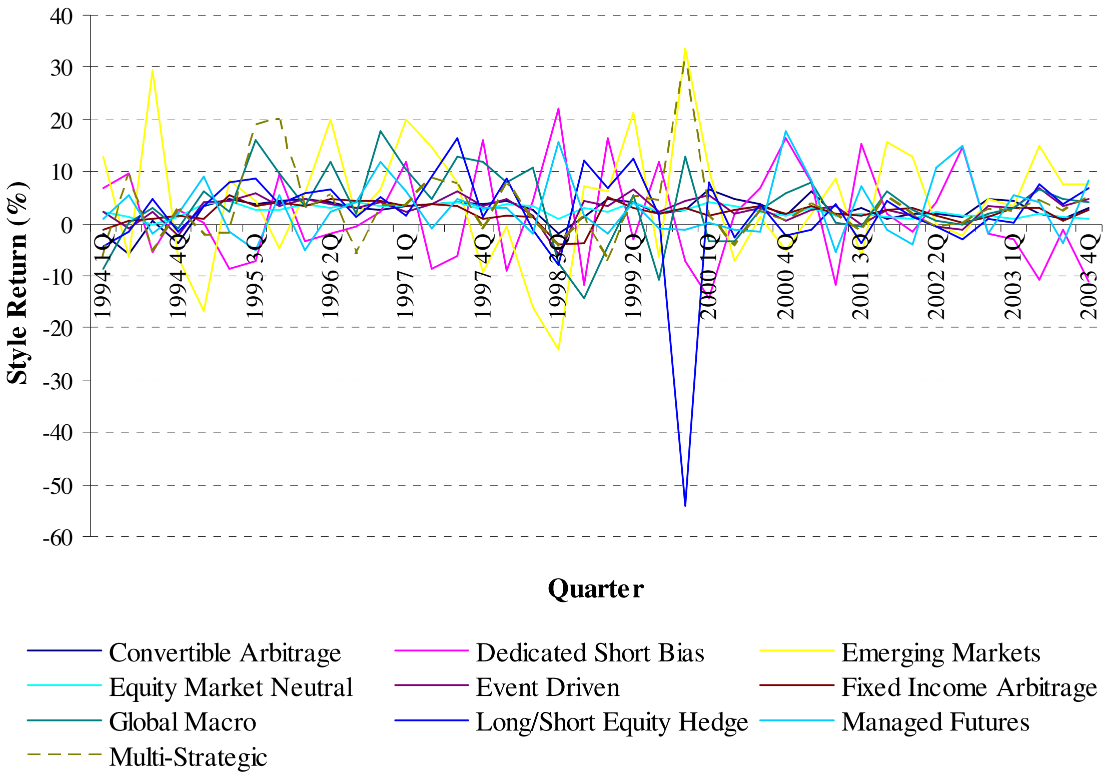
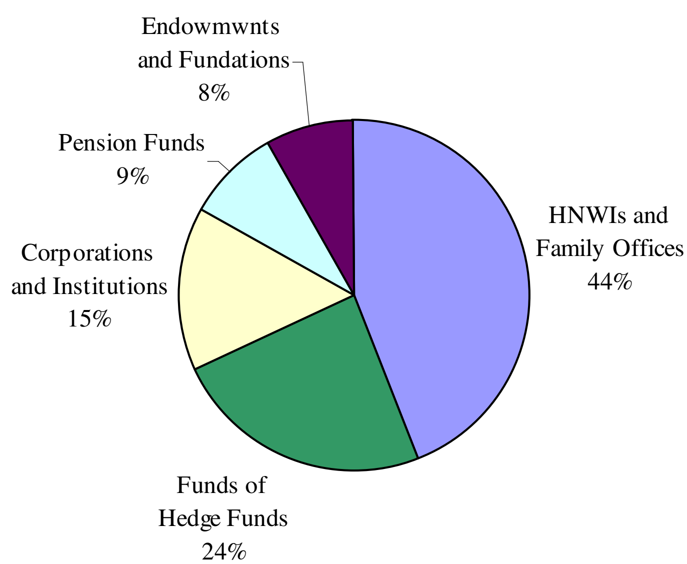


Figure 3: Style returns over time



Appendix 2: Hedge fund industry investor composition[9]



[9] From Francois-Serge Lhabitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd., page 35.

Appendix 3: Robustness - ADN 2004 style classification

Panel A: Style flows and style competition

The table reports coefficients of 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 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 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 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		