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 to more successful hedge fund investment styles of the recent past. Furthermore, we find evidence of competition between individual hedge funds of the same style. Funds outperforming their styles and funds with above style average inflows experience higher inflows in subsequent periods. One of the reasons for competition within same style funds is the investors' search for the best managers. The extremely high level of minimum investments limits the diversification opportunities and makes this search particularly important. Finally, we show that hedge funds' version of style chasing in combination with intra-style fund selection represents a smart strategy.

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1. Introduction

Hedge funds, like many other investment classes, are often classified by investment styles. Long-Short equity hedge, managed futures, event-driven and convertible arbitrage are among the most popular hedge fund investment styles of the past decade. The importance of style classifications grows with the number of individual assets or funds in an investment class. In huge investment classes, like stocks or mutual funds, a portfolio allocation decision based on a selection among styles is often preferred to a selection among individual assets. Today, the number of registered hedge funds far exceeds 10,000. Therefore, we expect that information regarding a hedge fund's investment style has an important impact on the investment decision. This 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 on the importance of investment styles (see, for example, Brown and Goetzmann, 2003). According to the style investing hypothesis (Barberis and Shleifer, 2003) investors categorize risky assets into styles and subsequently allocate money to those styles depending on the relative performance of the styles. There are a number of studies testing style investing for different financial sectors (see, for example, Barberis, Shleifer and Wurgler (2003), Pomorski (2004)). However, for our best knowledge, none of the existing papers studies style investing for hedge funds. Moreover, while some of the current hedge fund literature studies the role of investment style documenting its particular importance, and some investigates factors driving investment decisions, there is none that thoroughly examines the link between investment style and investment decisions. We propose to fill this gap by examining the way hedge fund style is taken into consideration in the investment decision process.

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

Second, the 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, for example, Agarwal, Daniel and Naik, 2004; Baquero and Verbeek, 2006; Ding, Getmansky, Liang and Wermers, 2007; and Li, Zhang and Zhao, 2007). However, none of the previous studies examine whether relative style information has an impact on individual fund flows. Given the huge number of hedge funds available, we expect that style information is an important factor in the choice for a particular hedge fund. In this study 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 the case of funds-of-funds, Fung, Hsieh, Naik and Ramadorai (2007) find strong evidence of diminishing returns to scale in combination with inflow of new money in the better performing funds. Naik, Ramadorai and Stromqvist (2007) show that capacity constraints affect future returns of some hedge fund strategies. Hedge fund investors are considered as a more sophisticated investor clientele when compared to mutual fund investors. However, hedge fund investors are confronted with liquidity restrictions due to, for instance, lock up periods. An investment decision in a hedge fund or hedge fund style cannot easily be reversed at a short term. This implies that such an investor needs to be more convinced of the appropriateness and the timing of the investment decision. Although capacity constraints for some strategies may negatively affect future returns at style level, a strategy of style chasing in combination with intra-style fund selection, may nevertheless be a well performing strategy. Therefore it is interesting to examine whether the more sophisticated hedge fund investors are behaving effectively when they increasingly invest in the most popular strategy of the recent past.

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

The remainder of this paper is organized as follows. In Section 2 we describe the data, and we present some summary statistics from our sample of hedge funds. In Section 3 we develop and motivate our hypotheses, while in Section 4 we formally test the hypotheses and perform a number of robustness checks. Section 5 concludes.

2. Data

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

We use quarterly data, which allows us to explore the short-term dynamics of investment and redemption behavior. Quarterly data reduces the patterns of serial correlation that characterize hedge fund returns when these are analyzed on a monthly basis (Getmansky, Lo and Makarov, 2004). We value total net assets (TNAs) per quarter for the most recent quarters available. Furthermore, we restrict attention to funds with a minimum of 5 quarters of return history and with quarterly cash flows available for at least 5 quarters. While the last selection imposes a survival condition, it ensures that a sufficient number of lagged returns are available in order to estimate our models. We exclude observations with extreme changes in TNAs. All observations with changes higher than 300 percent (there were 83 such observations) or lower than -90 percent (there were 44 such observations) are excluded. Our final sample contains 2,274 funds and a total of 33,203 fund-period observations. Our sample contains 229 funds at the end of the first quarter of 1994, accounting for about 27 billion US dollars in net assets, and 1,331 funds at the end of the last quarter of 2003, accounting for 195 billion.[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 (approximately 73%) make use of leverage, and 55% of the funds register that the fund manager invested personal capital.

[Please insert Table 1 about here]

[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 of 2003 (See Francois-Serge L'Habitant, 2007, "Handbook of Hedge Funds", John Wiley & Sons, Ltd., graph on the page 21, provided to the author by the Hedge Fund Research database).

According to the results of a 2003 survey conducted by the Alternative Investment Management Association, about half (47%) of hedge fund industry participants (consultants, investors, and managers) use one or more of the style classifications defined by outside classification systems, while only a very few (3%) argue that there is no way to classify hedge funds.[4] Nonetheless, there is no commonly accepted rule to categorize hedge funds. While the hedge fund industry was originally based on a single long-short strategy, today hedge funds use an abundance of different investment strategies. In our study we use the TASS style classification which is similar to one of the most widely accepted systems - CS/Tremont.[5] For robustness checks we also use the classification suggested by Agarwal, Daniel and Naik (2004). They determine four broad styles and we refer to this classification as the ADN styles. Alternative classifications exist as well (see, for example, Okunev and White (2003), Harri and Brorsen (2004)).

[Please insert Table 2 about here]

Table 2 presents the two style classifications, while Figure 1 displays the trend in assets under management for different TASS styles in the industry. The figure shows that the total net assets under management for most styles increased considerably over the sample period. For instance, the most popular style – *Long/Short Equity* – had about ten times the assets under management at the end of 2003 as it had at the beginning of 1994, and the greatest growth is observed in the *Equity Market Neutral* style which increased its holdings over the sample period by a factor of almost 45. At the same time, the difference in the growth rates of hedge fund styles indicates asymmetry in distribution of funds among different styles.

[Please insert Figure 1 about here]

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

[4] See Francois-Serge L'Habitant, 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 the European and Cogent Hedge databases.

the first half of the sample period, while it improves its share over the second half of the period.

[Please insert Figure 2 about here]

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

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

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

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

where $R_{j,i,t}$ is the return of fund *j* related to style *i* and realized during quarter *t*. Table 3 reports descriptive statistics of the style return for each of the hedge fund styles over the sample period.

[Please insert Table 3 about here]

Additionally, 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 losing styles in terms of raw returns. For example, in the middle of 1997, the *Emerging Market* style had the highest returns and *Dedicated Short Bias* the worst, while at the end of 2000 the situation reversed: *Dedicated Short Bias* was among the leaders while the *Emerging Market* style was among the losers. Moreover, Figure 3 indicates that a time prosperous for one style might be destructive for other styles. For instance, while at the end of 1999 the *Emerging Markets* style's return jumped to more than 30%, *Long/Short Equity Hedge*'s return dropped by more than 50%.

[Please insert Figure 3 about here]

Table 4 provides descriptive statistics for investment style flows over the sample period. This table illustrates that the average flows into styles are mostly positive. Moreover, none of them exceeds the level of 10%. Interestingly, while this consistent moderate average level might seem to indicate stability of the style flows, when examined over time, the flows are far more volatile. During our sample period, each style went through both a period of dramatic outflow and a period of extremely high inflows. For example, the *Equity Market Neutral* style had the highest level of outflows (-32.66%), losing almost one third of its assets, while in a later period it increased its size by more than one third (36.12%).

[Please insert Table 4 about here]

3. Hypotheses and Methodology

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

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

A number of hedge fund papers investigate the style-performance relation. Agarwal, Daniel and Naik (2000) conduct a so-called generalized style analysis to examine the risk-return tradeoffs.[6] The authors report that directional strategies demonstrate lower Sharpe

[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

ratios and higher downside risk as compared to non-directional strategies. Overall, the authors find that the risk exposures are mostly consistent with the investment objectives of the different hedge fund strategies. Amenc, Faff and Martellini (2003) show evidence on significant diversification benefits achieved by adding hedge funds, diversified at style level, to an investors' portfolio. Brown and Goetzmann (2003) find that investment styles explain about 20% of the cross sectional variability in hedge fund returns. Based on this finding, the authors conclude that appropriate style analysis and style management are important elements in the investment decisions of hedge fund investors.

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

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strategies are designed to benefit from broad market movements. These two categories potentially have very different applications: the directional strategies helping one achieve the desired asset allocation while the non-directional strategies enabling one to profit from security selection." (Agarwal, Daniel and Naik (2000)).

raw returns. Therefore, for the analysis based on risk-adjusted returns or alphas our sample reduced to 9,898 fund observations for 883 funds.

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

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

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

$$sFlow_{i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times sRnkFlow_{i,t-n} + \sum_{n=1}^{4} \beta_{2,n} \times sRnkR_{i,t-n} + \beta_3 \times sRisk_{i,t} + $$

$$+\beta_4 \times sSize_{i,t} + \varepsilon_{i,t} \ , \tag{3}$$

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*.[7] $sRisk_{i,t}$ is the risk of style *i* calculated as the standard deviation of the style's quarterly return measured over the previous four quarters. $sSize_{i,t}$ is a control variable for size of the style and calculated as the natural logarithm of the total net assets under management for style *i* at quarter *t*.[8]

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

[7] To exclude multicollinearity problem, we first compute correlations for all of the variables included in the analysis. We confirm that the estimated correlations are low enough to allow performance of the discussed analysis.
[8] We perform a robustness test controlling for time effect. We confirm that our results stay qualitatively the same.

(Agarwal, Daniel and Naik, 2004) exists at style level as well. We expect that the relative past performance of an investment style creates initial interest in that style, while subsequent investments attract even greater investments (money follows money). "Money follows money" seems to be especially powerful in the hedge fund industry. Style flows reflect the beliefs of investors in the future potential of a specific style. In the case of the hedge fund industry, investors' beliefs are especially meaningful, since this industry is characterized by a relatively high concentration of sophisticated investors. This is in line with the finding of Ding, Getmansky, Liang and Wermers (2007) who show that in the hedge fund industry, a fund's flows predict its future performance.

At the individual fund level, hedge fund literature suggests a variety of factors determining investment decisions. Past performance as well as fund characteristics such as the manager compensation scheme, fund manager characteristics, and presence of share restrictions- appear to have a significant impact on fund flows (see, for example, Agarwal, Daniel and Naik, 2004; Goetzmann, Ingersoll, and Ross, 2003; Baquero and Verbeek, 2006; Ding, Getmansky, Liang and Wermers, 2007; Li, Zhang and Zhao, 2007). Most studies examining the flow-performance relation report a positive relationship between past performance and money flows into and out of the hedge funds (see, for example, Agarwal, Daniel and Naik (2004), Baquero and Verbeek, (2006)). Using annual time intervals, Agarwal, Daniel and Naik (2004) show that the superior performance of an individual hedge fund in a given year lead to higher money-flows into this fund in the succeeding year. Moreover, this relation is found to be convex. Further, the authors demonstrate that persistence of good past performance can be associated with even higher money-inflows. The authors also find that the future performance of larger individual hedge funds with greater inflows tends to be worse. Fung, Hsieh, Naik and Ramadoria (2007) examine the flow-performance relation in the context of fund of funds (FOFs). They document that alpha producing FOFs have substantially higher and steadier money inflows than their less successful rivals. Based on this finding, they conclude that capital inflows influence funds' ability to generate alpha in the future. Most recently, Ding, Getmansky, Liang and Wermers (2007) show that share restrictions have an important effect on the shape of the flow-performance relation. In the absence of share restrictions, a convex relation is found, while in case of share restrictions, the relation appears to be concave. The authors also demonstrate that while in the hedge fund industry fund flows predict future hedge fund performance, this effect is weaker in funds with share restrictions. However, none of the studies cited above examine the influence of style information on hedge fund money flows. Given the huge number of hedge funds available, we expect that style information is an important factor in an investor's choice of a particular hedge fund.

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

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

We specify the following regression equation:

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

where $fFlow_{j,i,t}$ are the flows of fund *j* related to style *i* at quarter *t*. $fRnkFlow_{j,i,t-n}$ is a dummy variable for measuring a fund's popularity within its style, that takes a value one if the fund has above average style flows in the corresponding quarter *t-n*. $fRnkR_{j,i,t-n}$ is a dummy variable for measuring a fund's success within its style that takes a value of one if the fund has above average style performance in the corresponding quarter *t-n*. $fFlow_{j,i,t-n}$ are the lagged flows of fund *j* related to style *i*. $fR_{j,i,t-n}$ is the raw or risk-adjusted return of fund *j* related to style *i* at quarter *t-n,* and $X_{j,t}$ is a vector of characteristics of fund *j* related to style i such as risk of the fund, size of the fund, and other characteristics considered as constant over the sample period.[9] $sRnkFlow_{i,j,t-n}$ is the rank of the flows of style *i* at quarter *t-n,* while $sRnkR_{i,j,t-n}$ reflects the rank of the performance (measured as raw return or risk-

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

adjusted return) of style i at quarter t-n. In keeping with our second hypothesis, we expect coefficients for the more popular and for the better performing funds, within their styles, to be significant and positive. Significant coefficients for both these variables would indicate that there is no direct competition among hedge funds of different styles, but rather competition between them via styles. More specifically, significant coefficients of these variables would imply that two funds related to different styles and having all the same characteristics except that one of them is among the leaders in its style while another is among the losers in its style will have significantly different flows in subsequent periods.

A third and related question of interest is whether the strategy of chasing the best performing and most popular investment style, and subsequently investing in the best performing funds within that particular style is a smart strategy for investors. Berk and Green's (2004) model of active portfolio management predicts diminishing returns to scale. The inflow of money into the best performing funds affects the performance negatively due to a limited number of profitable investment opportunities. Naik, Ramadorai and Stromqvist (2007) show that capacity constraints in some hedge fund strategies explain the decline in the alphas of those strategies. In contrast to mutual fund managers, individual hedge fund managers have the option of closing a fund to new investors. In this way they can circumvent the challenge of having to invest significant additional money funds, potentially affecting the fund performance negatively. However, in line with Naik, Ramadorai and Stromqvist (2007), we expect that the inflow of new money to a particular successful style affects the competition between funds within that style by leading to an increase in the number of funds offered with that same style. This would lead to a diminishing performance of the style in general as shown by Naik, Ramadorai and Stromqvist (2007). However, this outcome does not necessarily imply that the strategy of investing in the best performing and most popular investment style at a certain moment in combination with intra-style fund selection is not a profitable strategy. Our third hypothesis is formulated as follows:

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

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

$$fR_{j,i,t} = \beta_0 + \sum_{n=1}^{4} \beta_{1,n} \times fRnkFlow_{j,i,t-n} + \sum_{n=1}^{4} \beta_{2,n} \times fRnkR_{j,i,t-n} +$$

$$+ \sum_{n=1}^{4} \beta_{3,n} \times fFlow_{j,i,t-n} + \sum_{n=1}^{4} \beta_{4,n} \times fR_{j,i,t-n} + \gamma' X_{j,t} +$$

$$+ \sum_{n=1}^{4} \beta_{5,n} \times sRnkFlow_{i,j,t-n} + \sum_{n=1}^{4} \beta_{6,n} \times sRnkR_{i,j,t-n} + \varepsilon_{i,t}, \tag{5}$$

where $fR_{j,i,t}$ is the raw return or risk-adjusted return for fund *j* related to style *i* at quarter *t*. $fRnkFlow_{j,i,t-n}$ is a dummy variable for within style popularity of a fund that takes a value of one if the fund has above average style flows in quarter *t-n*. $fRnkR_{j,i,t-n}$ is a dummy variable for within style winning funds that takes value one if the fund has above average style performance in quarter *t-n*. We control for individual fund characteristics such as past flows and past performance, risk and size.[10] $fFlow_{j,i,t-n}$ represents the flows of fund *j* related to style *i* in quarter *t-n*. $fR_{j,i,t-n}$ is the raw return or risk-adjusted return for fund *j* related to style *i* in quarter *t-n*. We also control for relative style characteristics. $X_{j,t}$ is a vector of fund characteristics such as risk and size, while $sRnkFlow_{i,j,t-n}$ is the rank of the flows of style *i* in quarter *t-n* and $sRnkR_{i,j,t-n}$ is the rank of performance of style *i* in quarter *t-n*. To evaluate hypothesis 3, we test whether better performing and more popular intra-style funds tend to produce higher performance in subsequent quarters.

4. Style Chasing

Our first question is whether relative style performance and relative style popularity affect the money flows to a specific hedge fund investment style. Column (1) of Table 5 presents the estimation results of Equation (3) when performance is measured by raw style returns, while Columns (2) and (3) show the results when performance is measured by risk-adjusted returns based on the corresponding models. In the case of raw style returns, the results reveal that the coefficients of the first three lags of relative style flows and the coefficient of the first lag of relative style performance are significant and positive. Moreover, these coefficients are economically significant. For instance, an increase in the style flow ranking of merely one point contributes 0.8% to the next period style flows.

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

Furthermore, an increase in the style performance ranking of one point increases next period style flows by more than 0.3%. These results suggest that, in keeping with *Hypothesis 1*, popular and better performing styles are rewarded with higher inflows in subsequent periods. In addition, the results show that the impact of style popularity, as measured by ranking past style flows, persists for a longer term than the effect of past style performance. While style popularity boosts style flows for the next three quarters, the effect of relative style performance holds for just a single quarter, and thus is considerably weaker. It appears that the risk associated with a particular hedge fund investment style has a dampening effect on the money flows to that style. When we measure performance as a risk-adjusted style return, we find similar results for past style popularity. However, the impact of lagged relative style performance is no longer significant. Apparently, even sophisticated hedge fund investors consider raw returns as more relevant than risk-adjusted returns in their allocation decision to particular hedge fund investment styles.

[Please insert Table 5 about here]

To compare the explanatory power of relative style flows and relative style performance, we run separate regressions for each of these variables[11]. The explanatory power of the regression with relative style flows is almost 18 percent, while that of the regression with relative style performance is only around 5 percent. This difference shows that style popularity has a stronger effect on future style flows than relative style performance. These results of our style level analyses show that the better performing and more popular styles are rewarded with higher inflows in the subsequent periods. These findings support the claim that there is style chasing in the hedge fund industry. Apparently, investors divide hedge funds into styles according to the fund's investment strategy, and increasingly invest in the better performing and popular styles. These results are consistent with the style investing theory of Barberis and Shleifer (2003).

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

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

If this would be the case, we would observe low correlation between relative performance of fund computed with respect to performance of the rest of funds combining the industry and relative performance of fund estimated with respect to performance of other funds in the style to which a particular fund is related. Correspondingly, the correlation between fund popularity measured with respect to this of all hedge funds and the popularity calculated with respect to popularity of funds related to the same style as that particular fund would be low as well. However, statistics summarized in Table 6 reveals that the discussed correlations are rather high, weakening, thereby, the direct fund competition argument. Further, we investigate the style chasing effect at the individual fund level, and show that there is no direct competition among individual funds, but only competition through styles.

[Please insert Table 6 about here]

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

Table 7 summarizes the results of the estimation of Equation (4) in which we test whether the intra-style relative flows and relative performance of hedge funds positively affect the inflows into the individual funds. Column (1) shows the results when performance is measured by raw returns, while Columns (2) and (3) show the results for risk adjusted returns calculated based on the three-factor Fama-French and the seven-factor Hsieh-Fung models respectively.

[Please insert Table 7 about here]

In the table we consider three sets of variables, intra-style, fund specific and general. The results in Column (1) demonstrate that the intra-style coefficients for all four lags of both – intra-style popularity and intra-style winner as measured by raw returns– are highly significant and positive. This suggests that, in line with *Hypothesis 2*, more popular and better performing funds within a style attract significantly higher money flows than the less popular and poorly performing ones. Intra-style popularity appears to have stronger impact on future flows than performance: flows to a popular fund are expected to be approximately 7% higher in the subsequent quarter than flows to an unpopular one, while flows to a well-performing fund will be granted with an additional 3.5% compared to a poorly performing one. In addition, the results show that the effect of intra-style popularity and performance diminishes over time. For both variables, coefficients of the first lags are more than three times higher than these of the forth. The estimates for the fund specific variables are in accord with results found in existing hedge fund literature. Lagged fund returns have a positive impact on the inflows to the funds, while larger and riskier funds receive less money than otherwise similar funds. The estimates for the general variables show that style popularity has an additional positive impact on the money flows towards a fund. Although the coefficients of the first three lags of relative style popularity are significant and positive, they have comparatively weak economic impact on fund flows. However, should the fund style's popularity move up one position in rank, the fund could expect a 0.55% additional inflows. On the other hand, none of the coefficients of relative style performance are statistically significant. For risk-adjusted returns we find similar results. As we found in the analysis at the style level, performance measured by risk-adjusted returns has marginal impact on individual fund flows. The significant coefficients for intra-style popularity and performance are in keeping with our assertion as to the absence of direct competition among hedge funds, and thereby confirm the presence of inter-style competition. Furthermore, the results show that the effect of style competition deteriorates at the intra-style level.

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

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

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

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

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

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

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

In Table 8 we present results of the analysis testing the influence of style popularity on the number of new and liquidated funds within a style (Panels A and B of Table 8 respectively). In keeping with our predictions, the effect of style competition for investors' money on the number of newly founded funds is not detected. At the same time, the results reveal a negative relation between past style popularity and the number of liquidated funds within the style, implying that higher style popularity predicts a lower number of liquidated funds within the style in the subsequent period. This result is in keeping with previous studies examining factors affecting survival probabilities (see, for example, Baquero, Ter Horst and Verbeek, 2005).

[Please insert Table 8 about here]

Table 9 reports the results of Equation (5). The results of the regression analysis show that the coefficient of the second, third and fourth lags of the best intra-style performers are significant and positive. These findings indicate that funds outperforming their style tend to perform better in the subsequent periods. The effect of the relative performance of the past half a year appears to be the strongest. Thus, a fund that outperforms its style could be expected to have a return over the next half year that is 1.13% higher than a fund that underperforms its style. It should be noted that the past half year relative performance has the strongest impact on fund flows as well. This result testifies to the effectiveness of hedge fund investors' form of style chasing.

Furthermore, the regression results show that the coefficient of the first lag of intra-style popularity is highly significant and positive. This suggests that intra-style popular funds show significantly better performance in the next quarter. This result contradicts to Berk and Green's model that predicts diminishing returns to scale. Thus, controlling for fund and style characteristics, it appears that fund's popularity within its style will lead it to outperform an unpopular fund within the same style by 0.59%. The effect of longer lags of intra-style popularity is less clear. Their coefficients are twice lower than the first lag coefficient, and one of them is negative. However, as previous results show, investors take intra-style fund popularity into consideration mostly over a half year horizon (see Table 7). Thus, in keeping with our prediction, in the hedge fund industry, style chasing implemented together with the search for the best funds within a particular style appears to be a successful strategy.

[Please insert Table 9 about here]

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

As is mentioned in Section 3 of this paper, statistics on the hedge fund industry shows that the majority of its participants use style classifications. Nonetheless, there is no commonly accepted categorization of hedge funds strategies. In our study, we use the style classification provided by TASS to perform the main analysis. Since this style classification is not the only one common in the hedge fund sector, we go through all the steps of our analysis a second time, this time applying the style classification suggested by Agarwal, Daniel and Naik (2004). The authors use an extensive database which includes data provided by different vendors, each of whom uses his favorite style classification. To define a common classification for their dataset the authors follow the approach of the studies of Fung and Hsieh (1997) and of Brown and Goetzmann (2003), which demonstrate that hedge fund returns include distinct style factors. The authors thereby reclassify all funds in their database into four categories (see Table 2). This broad classification may serve as a useful common denominator for the style classifications used by the main information services providers.

Appendix 1 reports the results of the analysis based on the ADN style classification. As illustrated by the appendix, these results are in keeping with those arrived at using the TASS classification, the style related coefficients at both the style and the individual fund levels are slightly higher than the corresponding coefficients of the analyses based on the TASS classification. Most importantly, these results provide strong support for the findings of our main analysis: the considerable effect of style on investment decisions in the hedge fund industry.

5. Conclusion

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

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

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

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Table 1
Descriptive Statistics of Cross-sectional Characteristics of Individual Hedge Funds

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

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

Table 2
Hedge Fund Style Classifications: TASS versus ADN[12]

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

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

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

Table 3
Descriptive Statistics of Style Return

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

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

Table 4
Style Investment Flows over the Sample Period

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

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

Table 5
Style flows and style competition

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

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

Table 6
Correlation Matrix

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

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

Table 7
Fund Flows and within Style Competition of Funds

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

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

Table 8
The Effect of Style Popularity on Number of New/Liquidated Funds within Style

Panel A:

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

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

Panel B:

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

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

Table 9
Fund Performance and Hedge Fund Version of Style Chasing

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

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

Figure 1

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

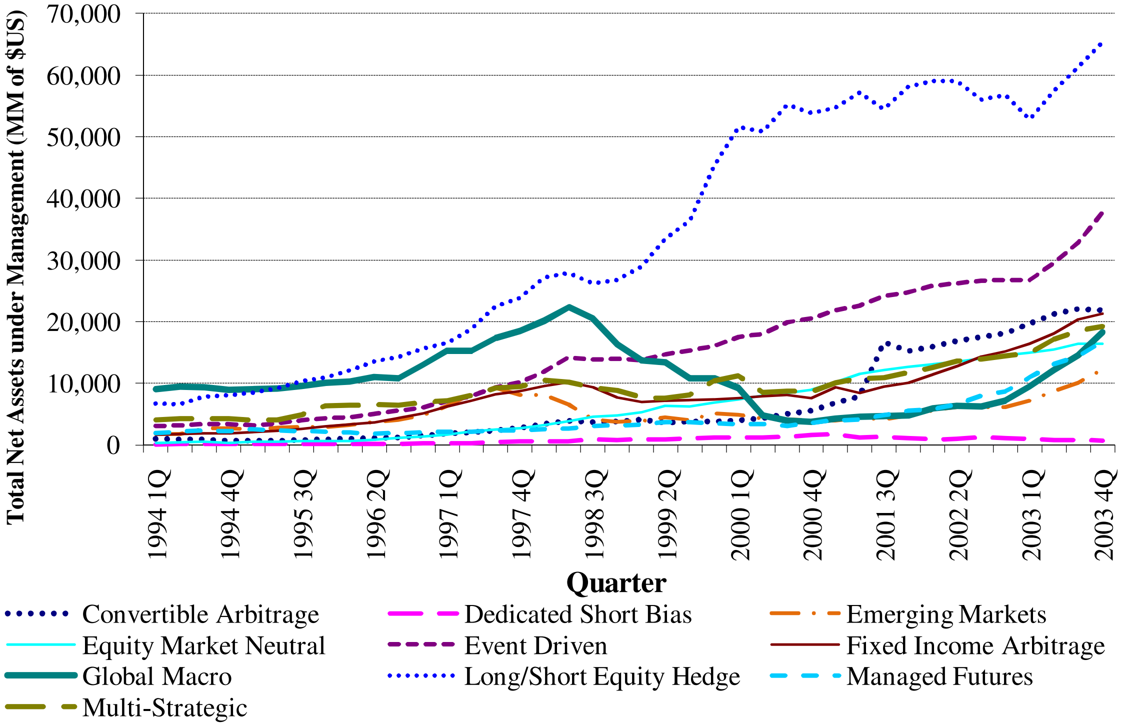


Figure 2

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

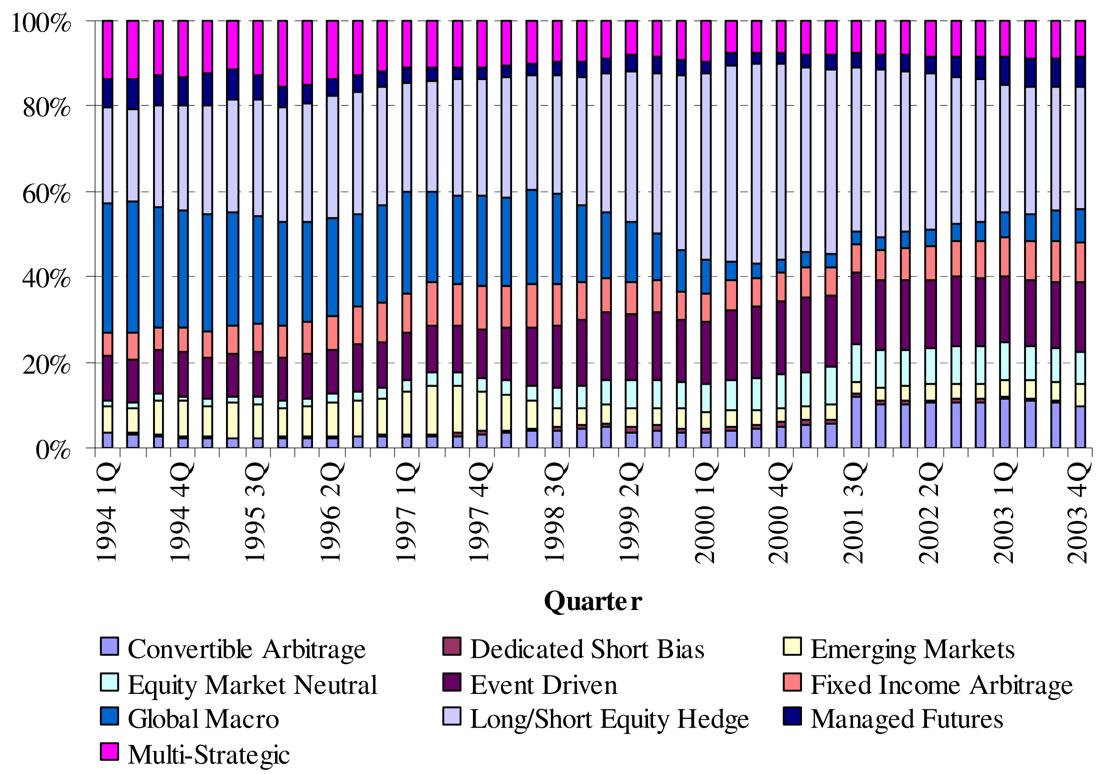
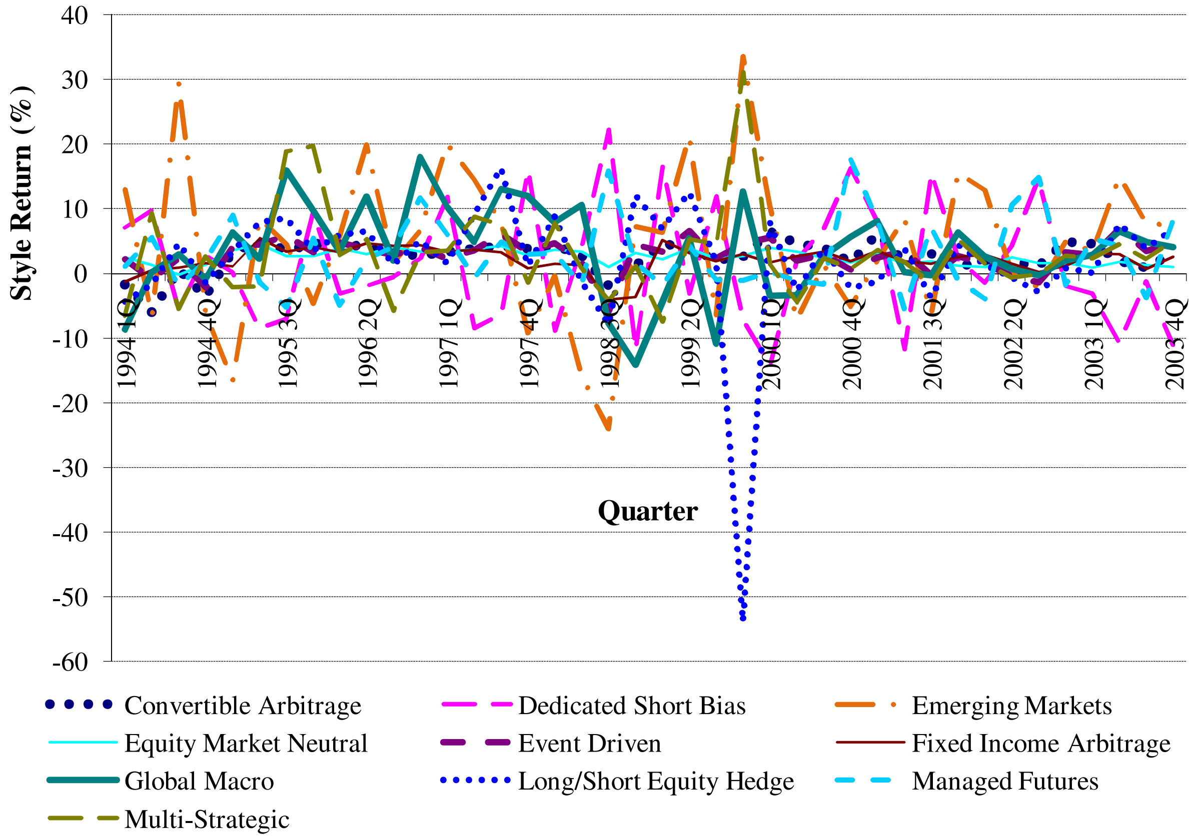


Figure 3
Style Returns over the period between January 1994 and December 2003



Appendix 1
Robustness - ADN 2004 style classification

Panel A: Style flows and style competition

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

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

Panel B: Fund flows and within style competition of funds

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

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