Style Investing:
Evidence from Hedge Fund Investors*

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Abstract

This study tests the hypothesis that one component of investors' allocations across hedge funds takes place at the style level as a result of extrapolative expectations. Using a sample of 1543 hedge funds between 1994 and 2004, we decompose the allocation process of hedge fund investors between style allocation and fund selectivity. Our contribution is twofold. First, we find evidence that the aggregate of investors actively shift their allocations across style categories by chasing the winning styles in the previous one to three quarters. These results suggest that investors perceive styles as substitutes to each other, irrespective of the risk-return properties of each style category. Second, we do not find evidence of style-timing abilities of hedge fund investors, nor indications of momentum in style index performance at quarterly horizons. This suggests that the chasing-the-winner strategy among styles reflects correlated sentiment of investors, consistent with the style-investment hypothesis. Overall, our study raises concerns that, despite growth, capital is inefficiently allocated across hedge funds.

Keywords: hedge funds, style investing, aggregate money flows, smart money, investor sentiment.

JEL-codes : G11, G23, G1

1 Introduction

Classifying assets into categories or "styles" provides investors with a simple framework to organize their allocation decisions.[1] Recent theoretical models of aggregate capital flows in financial markets make the non-trivial assumption that investors' allocations at the style-level are based on relative past performance. In these models investors exhibit extrapolative expectations and form their beliefs about future performance by learning from past performance information at the style level exclusively. In this view, style investing is unrelated to fundamentals and it simply amounts to chasing the styles with better prior records. Put differently, investors' coordinated shift of capital from one category to another is the result of correlated sentiment vis-à-vis styles performance. The style-chasing hypothesis is a key feature, for instance, in the model of Barberis and Shleifer [2003] who show how style-driven demand creates comovement and temporary mispricings of securities within the favored categories while it imposes an externality with opposite repercussions in less favored style categories[2]. Also Shleifer and Vishny [1997] make explicit the notion of style-chasing as a result of extrapolative expectations. However, their model captures the idea that capital from individual and institutional investors flows to different markets or style categories often via professional fund managers specialized in each style or market, like hedge funds. In this case style investing translates into chasing the best performing category of fund managers. In their model, the coordinated response of money flows to past aggregate performance of fund managers in a given style regardless of the actual opportunities available in that market conduces to the perverse effect of constraining managers' ability to counteract mispricings of securities.[3]

On this account, the purpose of the present paper is twofold. First, we empirically test the underlying assumption of the models of style investing. Concretely, we test the hypothesis that hedge fund investors chase hedge fund style-categories. Our second aim is to document the extent to which style investing is indeed the result of uninformed

[1] For example, the typical top-down approach implemented mostly by institutional investors, starts with an allocation policy at the style level followed by within-style selection.

[2] Barberis and Shleifer [2003] combine extrapolative expectations with a constraint on investors' allocations to the broadest asset classes (i.e. cash, bonds and stocks) leading investors to shift their capital from poor performing styles towards good performing styles. Essentially, their model focuses on the cross effects of a coordinated demand driven by a common sentiment factor vis-à-vis style categories.

[3] In their model arbitrageurs in one segment gain or lose money under management depending on their performance with respect to other segments. They refer to this mechanism as "performance-based aribitrage (PBA). Notice however, that their model does not address the cross effects of style investing (which is the focus of Barberis and Shleifer [2003]), but focuses on the particular relation between funds and past relative performance of a given segment and how sentiment-driven flows place a constraint on arbitrageurs while reducing their investment horizon, especially after adverse performance. Conversely, the model of Barberis and Shleifer [2003] makes abstraction of the intermediate role of professional fund managers specialized in a given style.

supply of capital. If this is the case, style driven flows should be uncorrelated with future style performance. If, on the contrary, investors are well informed, they should be able to timely direct their money into the best performing categories in the future and out of the poor performing categories. Therefore, we also test whether past style performance is informative about future performance, in a way that style-chasing could be justified, and whether there is any indication of smart money at the style level.

Several considerations suggest that especially hedge fund investors are likely to follow simple feed-back trading strategies based on past performance of investment styles. On the one hand, a large portion of capital inflows to hedge funds, currently about 50%, comes from institutional investors who tend to follow systematic portfolio allocation rules in a way they can later justify their actions to those monitoring them (as argued by Lakonishok et al [1992]). On the other hand, given the opacity and limited regulation of the industry, investors are in general poorly informed. Further, the arbitrage strategies typically used by hedge fund managers are difficult to evaluate and their understanding requires financial expertise. Under these circumstances investors may tend to fall back on the use of style classifications together with a simple decision rule based on past performance as powerful means to simplify the processing of complex and noisy information. Finally, at least one study has provided evidence that hedge fund investors misperceive patterns of performance persistence of individual funds, and overinvest accordingly (see Baquero and Verbeek [2006b]). The question arises whether or not investors display any cognitive bias also in their perception of aggregate performance at the style level. For instance, DeBondt [1991, 1993] describes the results of experiments in which both professional and naïve investors tend to see trends in aggregate market indices, presumably as a result of anchoring and representativeness. While naïve investors expect continuation, sophisticated investors expect a reversal in the trend.

The empirical evidence of style chasing is relatively scarce so far.[4] At the individual fund level, Cooper et al [2004] present evidence of style investing strategies among mutual fund investors. Money flows are attracted by mutual funds that change their names in order to suggest a different style focus. Their results indicate that funds with previous poor performance are the most inclined to change names. But they also find little evidence that after the name change funds indeed changed of allocation strategy. Among the few studies on aggregate money flows to investment funds, only two of them have explicitly attempted to link money flows to the performance of styles. The study by

[4] Several empirical studies have rather focused on the theoretical implications of style investing. For example, Teo and Woo [2002] test one of the predictions of Barberis and Schleifer [2003], namely that value and momentum strategies are profitable. Barberis, Shleifer and Wurgler [2002] test the prediction of comovement by looking at inclusions of stocks in the S&P500 index. They find evidence that the beta of stocks and their correlations with the index increase after the inclusion, consistent with the idea that the index itself represents a style category.

Lettau [1997] focuses on aggregate flows to different mutual fund categories and assumes adaptive learning of investors at the style level because of bounded rationality. He finds evidence that aggregate past performance determines the movements of capital into and out of mutual fund categories, especially for the riskier categories (e.g. aggressive growth and growth). Further, the sensitivity is higher for poor performing categories. Also Pomorski [1994] examines whether mutual fund flows chase styles, while using different possible style classifications of mutual funds for his test. He finds that aggregate money flows to a given category are positively related to prior returns in that category and negatively related to those in other categories, consistent with the feed-back trading model of Barberis and Shleifer [2003]. However, at the individual level, the effect disappears. Flows are negatively related to styles and chase individual manager performance.[5]

The aforementioned studies at the aggregate level, though, suffer from two main drawbacks. First, a certain component of money flows, even at the aggregate level, reflect decisions motivated by individual fund manager evaluation. This component has not been isolated so far. Second, these studies have been conducted under the assumption that the style classifications considered in the test are the true asset classes that investors have in their minds. For this reason, Pomorski [1994] employs several criteria to define a style classification and construct an aggregate performance measure.

One contribution of our study is precisely to tackle these two issues. First, we employ hedge fund style indices which offer a neat and concrete way to identify styles as perceived by investors for an empirical test. In spite of the many criticisms they have faced, style indices are widely used by investors for several benchmarking-related purposes. Style indices are reported monthly and are followed closely by the investment community as the only available reference tool, albeit imperfect as we will discuss below. Second, we identify and isolate the component of flows related to individual fund selection by estimating first a cross-sectional model of money flows from style adjusted performance and other fund characteristics. From this model we obtain an estimate of expected money flows driven by fund selectivity while we link the aggregate residuals to the performance of style indices.

[5] Other studies of money flows at the aggregate level are Warther [1995], Brown et al [2000], Edelen and Warner [1999], which concentrate on the relation between money flows and the aggregate market, but do not study the cross effects between segments or styles. These studies also argue that money flows to investment funds, especially mutual funds are a proxy for investor sentiment. Warther [1996] for example examines the possibility that investors are, on aggregate, feed-back traders and invest by chasing aggregate stock returns. He also examines the effect of aggregate flows upon aggregate stock market returns, under the assumption of a price-pressure hypothesis. By modeling the times series of aggregate money flows, he separately analyzes the impact of expected and unexpected flows. While he finds evidence consistent with positive feedback trading, his results do not support the price pressure hypothesis.

We report two main results. First, we find evidence that investors chase the winning styles in the previous one to three quarters. Second, we do not find evidence that style-driven flows are related to subsequent style performance, nor indications of momentum in style index performance at quarterly horizons, which suggests that momentum investing is the result of a biased perception of style trends.

The remainder of the paper is organized as follows. The next section offers an overview of the main characteristics of style categories and style indices. Section 3 describes our data on individual funds and style indices. Section 4 isolates the style-allocation component from individual fund selectivity and tests the style-chasing hypothesis. Section 5 studies momentum in style index performance, while Section 6 tests the style-timing abilities of hedge fund investors. Finally Section 7 concludes.

2 Hedge Fund Indexation

This paper devotes attention to the style-level decisions of hedge fund investors. Specifically, we test the hypothesis that investors' allocations across style categories are determined by relative past performance. A primary requirement to test the style investment hypothesis is to have a well defined and unique set of style categories common to all investors. In the hedge fund industry, such a set of style categories can be concretely identified by a set of style indices. There are currently more than a dozen competing providers of hedge fund indices and sub indices reporting monthly figures. By reducing the vast array of trading and investment strategies pursued by fund managers to a handful of style categories, hedge fund indexation has tremendously simplified the evaluation of individual fund managers and the overall decision-making process of their investors. Accordingly, an allocation decision into hedge funds commonly proceeds in two distinct phases. Investors first determine the style category that better suits their investment objectives. In a second phase investors select funds within that specific category.

The first indices were launched in the early 1990's. Index providers are usually private investment advisors or database vendors such as CSFB/Tremont, who use their own datasets for construction of the index. Therefore each index reflects the characteristics of that particular universe, as there is little overlap of funds across datasets. More recently, a number of private firms traditionally involved in tracking and evaluating the aggregate market, such as S&P, have also started constructing their own index products.

Hedge fund indices have had a huge impact in the industry by helping disseminating the industry's overall performance among an expanding base of investors. They are widely used as the only available reference tool for comparison across managers and strategies.

Hedge fund index products are seen as guidelines for investing, facilitating the comparison across asset classes, but also for style analysis, portfolio analysis and portfolio construction. The last developments include investable hedge fund indices, which allow investors to have exposure to a well diversified portfolio of hedge funds with the additional advantage of being able to buy and sell the shares in the index in a secondary market. Before investable indexes existed, investors could only diversify across hedge funds through funds of funds, at a substantial liquidity risk.

Indices of hedge funds are generally constructed as a representative average of funds with a similar investment style. Developing a taxonomy of hedge funds is, however, a notoriously difficult task since hedge funds enjoy a distinctive flexibility in the types of investment strategies they can deploy. It is difficult to refer to a given hedge fund style as a homogenous group. Hedge fund managers' fickle behavior in moving into and out of different asset classes, their use of leverage and short selling, often with exposures to illiquid securities, makes the use of any index-based benchmarking questionable. In spite of that, several classification systems are currently in use in the industry, with large differences among them. There is no consensus yet on a unique standardized system.[6]

Hedge fund styles encompass not only categories of securities, which might include a geographic dimension (e.g. convertible securities, fixed income securities, equity, global, etc), but also a particular trading style (long short, short bias, arbitrage, market neutral, etc). Therefore, the performance of a hedge fund style index is not only a reflection of the performance of the underlying securities, as it is the case for mutual fund styles, but above all it reflects the effectiveness of the trading style.

One important caveat in the construction of a meaningful style classification is the quality and frequency of available data. Hedge funds commonly report their performance monthly, but most do so with a considerable delay given the complexity in the computation and deduction of incentive fees. Therefore, it is likely that by the date necessary for calculation of the index, funds have been unable to report or they have reported performance estimates to be revised later. Further, hedge fund reporting is voluntary, leading to selection biases and backfilling biases[7]. Funds with unusually good performance may have incentives to report, or to report earlier in order to attract further investors. On the other hand, established funds with good track records that have reached capacity limits may decide to close to new investments and self-select out of the database. Finally, hedge funds liquidate at relatively high frequencies, conducing to

[6] The Alternative Investment Management Association (AIMA) has deployed efforts in that direction and appointed a study committee for such effect.

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

survivorship biases in the construction of the index. Moreover data gathering problems might differ across strategies and periods.

The construction technology of indices of hedge funds has considerably evolved, becoming more rigorous, under increasing demand for indexing products from institutional investors. There are three broad weighting schemes used by most providers of hedge fund indices. An equally-weighted average, asset weighted average and percentile-based indices. The former is a simple average return of the constituent funds and it was the typical scheme used by the first indices as it does not require information on assets under management. It continues to be used by most indices today (MAR, S&P, VanHedge Fund Advisors, HFR, MSCI). A percentile-based index uses a percentile – usually the median, the 10th and 90th percentile - instead of the mean of the return distribution of the constituents, while TNA are not required either. They avoid the impact of extreme values in the returns of any of its constituent funds (Zurich Capital Markets index family, PerTrac Online index family). However, they do not reflect the actual dollar returns. Three providers of indices currently offer asset weighted schemes: Credit Swiss First Boston/Tremont (CSFB/Tremont), Morgan Stanley Capital International (MSCI) and Hedge Fund Research (HFR). A weighted scheme represents more accurately the actual dollar returns across their constituent funds.

Hedge fund indices and subindices have been subject of controversy, especially concerning the consistency of hedge fund classifications, the lack of transparency of the rules and techniques of construction employed by different index providers, and how these construction techniques deal with the limited data quality. It is not surprising that a large number of academic studies have focused attention on the impact of data-related biases, on the statistical properties of style indices, their consistency, and their actual usefulness for hedge fund allocation and portfolio analysis[8]. Brooks and Kat [2001] and Amenc and Martellini [2002] have documented heterogeneity in the information content of competing indices. For a given strategy, competing indices exhibit relatively low correlations, and very large differences in returns in some periods, especially in periods of crises[9]. Other studies have instead pointed out at the potential usefulness of indices. For example, using the TASS database, Brown and Goetzmann [2002] find that style categories account for 20% in the cross sectional variation of fund returns, indicating that

[8] See for example Amenc and Martellini [2001, 2002], Amenc, El Bied and Martellini [2003], Brooks and Kat [2001], Brown and Goetzmann [2003], Fung and Hsieh [1997, 2002]. In mutual funds, two relevant studies about consistency of style classifications are those of Brown and Goetzmann [1997] and Chen, Chan, Lakonishok [2002].

[9] Amenc and Martellini [2002] give the example of Long Short index in February 2000, between Zurich Capital Market index, ZCM, (20.48%) and Evaluation Associates Capital Markets, EACM, (-1.56%). Brooks and Kat[2001] also find large differences between index families, especially for macro and Equity Market Neutral indices.

the classification conveys some valuable information. Finally, by studying the time series of style index returns, Amenc and Martellini [2002] suggest that style tactical allocation is profitable.

It remains an open question how investors are actually driven in their allocation decisions by style-level information. In fact the financial press, industry newsletters and providers of hedge fund indices, offer periodic reports about the past performance and expected performance of style indices, they compare indices with each other and often highlight trends in the time series. The question arises whether investors on aggregate pay attention to such information and actively seek to time styles. If this is the case, it also remains to be clarified whether investors pay attention to absolute style index returns or compare style indices relative to each other. Are investors influenced by upward or downward trends of an index? Over which horizons is the information contained in an index relevant for an investor? And finally, does this information help investors to timely direct their money into the best performing categories and out of the poor performing categories? The following sections explore these interrelated questions and offer an assessment of the efficiency of capital allocation across hedge funds.

3 Data

Access to hedge fund data is one of the major limitations in hedge fund studies. Hedge funds are not complied to report their performance and holdings, as they are subject to limited regulation. Therefore, hedge fund datasets are based upon voluntary reporting, which gives room to several potential biases, as documented by previous researchers (see e.g. Baquero, Ter Horst and Verbeek [2005], Agarwal and Naik [2000], Brown, Goetzmann and Ibbotson [1999]). Given this major drawback, in order to make inferences about the portfolio of hedge fund investors as a whole, we require a representative sample that encompasses not only all investment styles but also a wide range of funds in terms of size, age, incentive fees, and location. Our dataset contains 1543 hedge funds spanning the period 1994Q4-2004Q3 (funds of funds and closed end funds are excluded). This is a sample of the TASS database that has been widely used in previous academic research. TASS provides a classification of mutually exclusive styles based on self-reported styles by managers and information contained in the offering memorandum. This classification matches the set of nine style indices provided by CSFB/Tremont. In this study we focus attention on quarterly returns and quarterly flows, although monthly data is available. However, a quarterly horizon is a natural investment horizon for hedge fund investors, as most redemption restrictions operate in a quarterly basis. Further, a powerful driver of investor sentiment is the coverage of media channels (e.g. press reports), and their attention focuses in general on quarterly returns. Table A1 in the appendix provides the total number of hedge funds in our sample per quarter and

Table I

Average Quarterly Performance of Style Indices, Market Indices and Funds in our Sample, between 1994Q4 and 2004Q3

Panel A gives a summary statistics of quarterly returns of CSFB/Tremont Hedge Fund indices over 40 quarters, from 1994Q4 till 2004Q3. We also include the performance of the S&P500 index and the 90 days T-bill for comparison. Panel B gives a summary statistics of quarterly returns of hedge funds in our sample sorted per style over the same period. In this panel, the category labeled "General Hedge fund index" contains the funds in our sample for which the investment style was not clearly identified. The sample consists of 1543 open-end hedge funds taken from TASS database that have a complete series of monthly total net assets (TNA), with a minimum of 6 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included.

Panel A: Summary Statistics of quarterly returns of CSFB/Tremont Indices and Market Indices

Index	Mean	Std. Dev.	Min	Max
Convertible Arbitrage	0.0271	0.0314	-0.0724	0.0972
Dedicated Short Bias	-0.0045	0.0984	-0.2008	0.2178
Emerging Markets	0.0189	0.1056	-0.2867	0.3066
Equity Market Neutral	0.0277	0.0161	-0.0002	0.0593
Event Driven	0.0290	0.0380	-0.1435	0.0839
Fixed Income Arbitrage	0.0182	0.0207	-0.0469	0.0483
Global Macro	0.0386	0.0583	-0.1046	0.1683
Long/Short Equity	0.0332	0.0617	-0.0781	0.2778
Managed Futures	0.0151	0.0632	-0.1046	0.1618
General Hedge fund index	0.0293	0.0417	-0.0887	0.1662
S&P500	0.0304	0.0884	-0.1728	0.2128
Tbill 90days	0.0098	0.0045	0.0023	0.0152

Panel B: Time-series averages of cross-sectional means per style in our sample

Style Category	Mean	Std. Dev.	Min	Max
Convertible Arbitrage	0.0278	0.0281	-0.0563	0.0785
Dedicated Short Bias	0.0086	0.1050	-0.1777	0.2242
Emerging Markets	0.0310	0.1132	-0.2770	0.2571
Equity Market Neutral	0.0206	0.0178	-0.0177	0.0539
Event Driven	0.0256	0.0328	-0.0997	0.0786
Fixed Income Arbitrage	0.0185	0.0254	-0.0496	0.0642
Global Macro	0.0244	0.0402	-0.0504	0.1153
Long/Short Equity	0.0337	0.0616	-0.0844	0.2150
Managed Futures	0.0231	0.0552	-0.1063	0.1449
General Hedge fund index	0.0246	0.0287	-0.0278	0.0893
All funds in our sample	0.0271	0.0350	-0.0502	0.1177

aggregate total net assets and cash flows. Table A2 provides summary statistics and a description of different fund-specific variables. Finally, Table A3 disaggregates the number of funds per period and per style category.

The CSFB/Tremont is an asset weighted index with 403 funds from the TASS database, rebalanced quarterly. The constituent funds are required to have a minimum TNA of $10 million, a one-year track record and an audited financial statement before being included.

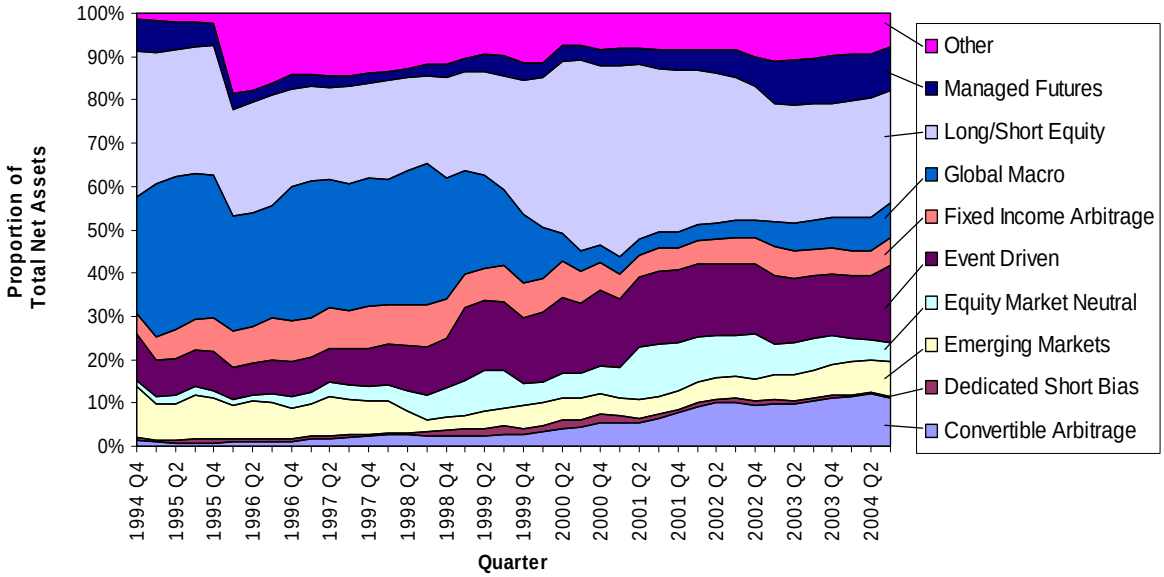
They are removed from the index for liquidation reasons or failure to meet reporting requirements. Some investment styles seek to time market movements and are referred to as directional strategies. Others seek to exploit arbitrage opportunities and are referred to as non directional. Table I provides a summary of quarterly performance of the general CSFB/Tremont hedge fund index and the nine sub-indices in Panel A, and the aggregate performance of hedge funds in our dataset sorted by style in panel B. Noticeably, there is wide dispersion in volatility across hedge fund categories. The most extreme returns are associated with Dedicated Short Bias and Emerging Markets styles, while Equity Market Neutral appears to be a relatively conservative category, with dispersion in returns far below the one of the market. Finally, Table I also indicates that both the general hedge fund index and the average hedge fund in our dataset have underperformed the stock market index over the sample period by 11 and 33 basis points per quarter respectively.

Figure 1 depicts the proportion of total assets under management shared by each category of funds in our database. The aggregate portfolio of hedge fund investors varies widely over time in terms of allocations across styles, sometimes dramatically. For instance, after 2002 the global macro strategy has experienced a sharp decrease in size, becoming almost unimportant. Our purpose in the following sections is to analyze more closely the behavior of aggregate money flows to better understand the motives underlying these changes in exposure to hedge fund categories.

Figure 1

Style Allocation of Hedge Fund Investors

Hedge funds are sorted per style category every quarter from 1994Q4 to 2004Q3. The figure indicates the variations over time of holdings of hedge fund investors across styles. Our sample consists of 1543 open-end hedge funds taken from TASS database.



4 Style level flows vs. fund selectivity

In this paper we argue that investors' learning occurs at two distinct levels. On the one hand, allocation decisions are powerfully driven by fund indexation, as many channels of information and advice within the industry regularly highlight the performance of style indices. On the other hand, individual fund evaluation via due diligence is a major and ineluctable task, as information hurdles resulting from limited regulation and disclosure prevent investors from a transparent assessment of fund managers. Our study concentrates on style level decisions and we are confronted to the problem of isolating as neatly as possible both components. Fund selection within a given style involves both a qualitative and quantitative analysis. Besides information on returns and assets under management, the TASS database provides a number of fund specific variables that are likely to be determinants of investors' final choice, like the structure of incentives, liquidity restrictions, geographic location, etc. Our methodology consists of estimating first a cross-sectional model of flows, in which we include on the right hand side only variables strictly related to fund selection. The main specification is the following:

$$Flows_{it} = \alpha + \sum_{j=1}^{6} \beta_{1j}.RnkUnrestricted_{it-j} + \sum_{j=1}^{6} \beta_{2j}.RnkRstricted_{it-j} + \beta_2.\ln(TNA_{it-1}) +$$

$$+ \beta_4.\ln(AGE_{it-1}) + \sum_{j=0}^{4} \beta_{5j}.Flow_{it-j} + \beta_6.\sigma_{it-1} + \gamma'.X_{i,t-1} + \lambda_t + \varepsilon_{it} \quad (1)$$

where $Flow_{i,t}$ represents the net percentage growth in fund i in period t, and $Rnk_{i,t-j}$ is the jth lagged relative style-adjusted performance as measured by a fund's cross-sectional rank. We distinguish between *restricted* and *unrestricted* ranks by allowing for interactions between lagged ranks and dummies accounting for limits to liquidity.[10] We include the size and age of the fund in the previous period, $ln(TNA_{i,t-1})$ and $ln(AGE_{i,t-1})$. $Flow_{i,t-j}$ is the jth lagged flow. $X_{i,t}$ is a vector of fund specific characteristics like management fees, incentive fees, managerial ownership. We control for time effects by including time dummies, denoted by λ_t, to capture economy wide shocks conducing to different average flows across quarters, as suggested by Table A1. Notice that our model does not include style-related variables, as our purpose is to capture such effects within the error term.

[10] In each quarter t, we define for each j-lagged rank and for each fund i :

$$Rank\ Unrestricted_{i,t-j} = Rank_{i,t-j} * (REDR_{i,t-j})$$
$$\text{and} \quad Rank\ Restricted_{i,t-j} = Rank_{i,t-j} * (1-REDR_{i,t-j})$$

where $REDR_{i,t-j}$ is a dummy variable that takes value 1 if redemption restrictions do not prevent outflows in quarter t in response to j-lagged performance given by $Rank_{i,t-j}$.

As it is standard in studies of money flows to investment funds, we measure flows as the growth rate in total assets under management of a fund between the start and end of quarter $t+1$ in excess of internal growth r_{t+1} of the quarter, had all dividends been reinvested. This definition assumes that flows take place at the end of period $t+1$.

$$CashFlow_{t+1} = \frac{Assets_{t+1} - Assets_t}{Assets_t} - r_{t+1}$$

This definition is also referred to as *normalized cash flows*. Alternatively, a measure of absolute cash flows, in dollar terms, is computed as a net change in assets minus internal growth.[11]

$$DollarFlow_{t+1} = Assets_{t+1} - Assets_t(1 + r_{t+1})$$

The previous model assumes that the selectivity process is similar across styles. More particularly, it assumes that the sensitivity of investors to past style-adjusted performance is independent of style. Our estimation results in Table II confirm previous evidence that money flows are directed to funds with better prior performance, and that past performance has a significant impact up to five lagged quarters or so. Liquidity restrictions, the age and the size of the fund are also important in the evaluation process of investors.[12]

Next, we obtain the residuals from the previous model, and we aggregate them per period and per style category under the assumption that both components, namely style allocation and fund selectivity are orthogonal. Put differently, we focus on the components of money flows that cannot be explained by fund-specific factors and are style-related. Table III reports estimates of a linear model explaining aggregate capital flows per style as measured by growth rates. We analyze whether differences in aggregate capital flows across styles are explained by past relative performance, by past style index returns, by the length of upward or downward trends in style performance or by any style-related fixed effects. Our sample contains 399 observations when all 10 styles indices are included and 359 observations when the general Hedge Fund index is excluded and we only consider the set of 9 subindices.[13] Table A4 in the appendix

[11] See Ippolito [1992], Gruber [1996], Zheng [1998], Del Guercio and Tkac [2002] for a discussion about the assumptions underlying these definitions of flows.

[12] See Baquero and Verbeek [2006a] for a detailed analysis of the impact of fund-specific variables on money flows.

[13] In fact we have 40 observations per style. However, we have identified one significant outlier corresponding to the *Convertible Arbitrage Strategy* in the last quarter of 2001, - a negative growth rate of -83%. The models presented in Tables III and IV exclude that single observation. When this observation is included in our model specifications, the impact of the individual variables remains for the most part unchanged but the explanatory power of the model is significantly affected, with a reduction in the R^2 to levels of 2 to 3%.

Table II

The Effect of Relative Style-Adjusted Performance Subject to Liquidity Restrictions Upon Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of flows subject to liquidity restrictions. The sample includes 1543 open-end hedge funds for the period 1994Q4 till 2003Q4. We measure cash flows as the change in total net assets between consecutive quarters corrected for reinvestments. We normalize this measure as a growth rate relative to the fund's total net assets of previous quarter. The independent variables that account for relative performance include six lagged fractional ranks interacting with dummies accounting for limits to liquidity. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's style-adjusted return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, the inverse of upside potential based on the entire past history of the fund and calculated with respect to the return on the US treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 39 time dummies (not reported). We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates of a model explaining growth rates	
Intercept	0.1549	(4.98)
Style-adj. Rank lag 1 Unrestricted	0.1063	(15.47)
Style-adj. Rank lag 2 Unrestricted	0.0801	(11.70)
Style-adj. Rank lag 3 Unrestricted	0.0605	(8.68)
Style-adj. Rank lag 4 Unrestricted	0.0462	(6.82)
Style-adj. Rank lag 5 Unrestricted	0.0192	(2.74)
Style-adj. Rank lag 6	0.0060	(0.88)
Style-adj. Rank lag 1 Restricted	0.1014	(6.15)
Style-adj. Rank lag 2 Restricted	0.0718	(3.42)
Style-adj. Rank lag 3 Restricted	0.0463	(2.82)
Style-adj. Rank lag 4 Restricted	0.0491	(3.04)
Style-adj. Rank lag 5 Restricted	0.0349	(1.90)
Ln(TNA)	-0.0124	(-8.91)
Ln(AGE)	-0.0171	(-5.08)
Flows lag 1	0.0557	(4.68)
Flows lag 2	0.0501	(5.83)
Flows lag 3	0.0114	(1.67)
Flows lag 4	0.0135	(2.21)
Offshore	0.0095	(2.25)
Incentive Fees	-0.0006	(-2.06)
Management Fees	-0.0084	(-3.96)
Personal Capital Invested	-0.0031	(-0.76)
Leverage	0.0149	(3.88)
Downside-Upside Potential Ratio	-0.0192	(-7.98)
Standard Deviation of Returns	-0.2663	(-3.82)
Number of observations	21841	
R^2	0.0811	

provides summary statistics of the relevant variables included in our model of aggregate flows. Over the sample period we have identified upward trends up to four quarters length and downward trends up to five quarters length. We capture the length of the trend with nine mutually exclusive dummies. We also include on the right hand side of our model a trend variable in order to account for the increase in the number of funds over time. We consider several alternative specifications corresponding to different ways of assessing past style performance. Recall that the style-investing hypothesis is rooted on the idea that investors compare styles with each other. Accordingly, in Panel A we include the structure of lagged style ranks as a measure of relative past performance, while controlling for upward and downward trends and style dummies. The style rank variable takes values between 1 and 9 and is obtained by ranking in each quarter the nine style indices based on their raw returns (therefore the *general Hedge Fund index* is excluded from the ranking).

According to our results, investors strongly respond to relative performance over the three lagged quarters. If one style index moves from the bottom to the top of the ranking in one period, the aggregate of funds in that style experience a significant increase of 5.6% in growth rates in the subsequent quarter, and a significant 11.6% increase over the next three quarters. Investors appear to be insensitive to the longer run in relative style performance.[14] They are also somehow insensitive to the length in style trends, although the coefficient for an upward trend of four quarters is negative and significant. This long upward trend occurs in two occasions only, in June 1997 and March 2001, both in the Dedicated Short Bias strategy. This gives some indication that investors in this very volatile strategy anticipate frequent reversals and act contrarian. Overall, the results of this first specification are consistent with the style-chasing hypothesis, whereby allocations are mostly directed to the styles with better prior performance and away of poor performing styles. Panel B reports estimation results when we include absolute performance instead of relative performance. In this case we also include the aggregate money flows for the group of funds without a clear investment style and we link it to the performance of the *general Hedge Fund Index*. This increases the number of observations from 359 to 399. The lagged structure of style index returns has also a significant impact upon growth rates but the pattern is less clear than with relative performance. The effect is mostly concentrated in the first lag. A 1% difference in style index returns accounts for nearly 0.25% increase in growth of the style in the next quarter. However, this model explains substantially less variation in the cross-section of aggregate growth rates compared to the previous specification, as indicated by the reduced value of the R^2. When both style ranks and style index returns are included (Panel C), ranks appear to capture all the impact on aggregate money flows.

[14] We have experimented with alternative specifications and additional lags do not have a significant impact on money flows.

An alternative way to account for past relative performance is to define a dummy for winning and losing styles. In a given period we define a style as a winner if it is placed in one of the top four ranks with respect to other styles. Otherwise the style is classified as a loser. Next, we count the number of consecutive quarters over which the style remains as winner (alternatively as loser). In this way, we identified winning streaks up to 13 quarters and losing streaks up to 10 quarters length. While in our first specification we have shown that the lagged style ranks manifestly have an influence on investors' decisions, here the question of interest is how investors do perceive a *precise* sequence in relative performance information. To analyze this, we create four dummies accounting for the length of winning streaks and 5 dummies for losing streaks. With one dummy we capture the effect of winning streaks of four quarters length or more. The last dummy accounts for losing streaks of more than five quarters length. The estimation results are presented in Panel D. It is apparent that investors follow a momentum strategy at the style level. Longer winning streaks attract significantly larger money flows, while longer losing streaks are associated with increasingly negative growth rates. For example, if a style index has underperformed most other indices for four consecutive quarters, it triggers significant negative growth rates of -4.54% compared to one-quarter streaks. If this style index remains one additional quarter as loser, growth rates reduce even further by 50 basis points.

In Table IV, we present estimates of our model when the dependent variable is aggregate residual dollar flows. The results are similar to those presented above. Dollar flows are sensitive to past style performance either in terms of style returns or style ranks, while investors clearly follow momentum strategies in response to winning and losing streaks. However, if we compare the R^2 of models in Panel A and B, we can conclude that ranks explain a substantially larger variation in cross sectional aggregate dollar flows. Moreover, styles at the top of the ranking attract $ 293 million more than styles at the bottom, according to Panel A, while according to Panel B, a differential of 1% in style returns attracts a further $ 9 million.

It is worthwhile to highlight that investors are apparently insensitive to upward and downward trends in the time series of index returns, but they are highly sensitive to sequences of relative performance measured in the cross section. Overall, our results strongly support the essential principle behind the style-investing hypothesis, namely that investors allocations depend on style performance relative to other styles. It is plausible however that style-chasing behavior is explained by investors having superior information or having performed a sophisticated analysis of style performance that motivates them to actively shift their capital across styles. If it is the case that investors exhibit style-timing abilities, it should be possible to identify a correlation between money flows and subsequent style performance. The next two sections explore this possibility.

Table III

The Effect of Style Performance
Upon Aggregate Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of aggregate money flows per style. Money flows are the residuals of the cross sectional model estimated in Table II explaining growth rates from style-adjusted performance and fund specific characteristics. We first obtain dollar flows per fund by multiplying the residuals by the total net assets in the previous period. Then we aggregate dollar flows per style and per period. Alternatively, we obtain an aggregate growth rate by dividing aggregate dollar flows by the aggregate total net assets in the previous quarter. The sample consists of 399 style-period observations between 1994Q4 and 2004Q3. The independent variables include three lagged style index returns, a trend variable, eight dummies accounting for the length of upward and downward trends in the style index and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The general hedge fund index is taken as reference category. We estimate our model by pooling all style-period observations. T-statistics are provided in parentheses.

	Model explaining style-driven growth rates							
	(A)		(B)		(C)		(D)	
Parameters	Coeff	t-test	Coeff.	t-test	Coeff.	t-test	Coeff.	t-test
Intercept	-0.0765	(-5.40)	-0.0098	(-0.97)	-0.0732	(-4.17)	0.0120	(1.05)
Style Rank lag 1	0.0070	(4.82)			0.0058	(2.92)		
Style Rank lag 2	0.0035	(2.31)			0.0044	(2.15)		
Style Rank lag 3	0.0043	(2.97)			0.0029	(1.44)		
Style Return lag 1			0.2520	(4.21)	0.0846	(1.05)		
Style Return lag 2			0.0318	(0.50)	-0.0730	(-0.87)		
Style Return lag 3			0.1902	(3.15)	0.0818	(0.98)		
Winning Streak 2							0.0109	(0.83)
Winning Streak 3							0.0098	(0.54)
Winning Streak 4							0.0372	(2.25)
Losing Streak 1							-0.0104	(-0.94)
Losing Streak 2							-0.0172	(-1.33)
Losing Streak 3							-0.0481	(-3.49)
Losing Streak 4							-0.0454	(-2.75)
Losing Streak 5							-0.0501	(-3.60)
Trend	0.0006	(2.13)	0.0005	(1.87)	0.0006	(2.15)	0.0006	(2.06)
Up 2 Quarters	0.0093	(0.81)	0.0203	(1.76)	0.0133	(1.11)	0.0049	(0.43)
Up 3 Quarters	0.0045	(0.23)	0.0122	(0.67)	0.0072	(0.37)	0.0037	(0.19)
Up 4 Quarters	-0.0880	(-2.02)	-0.1019	(-2.25)	-0.0914	(-2.08)	-0.0905	(-2.04)
Down 1 Quarter	0.0018	(0.18)	0.0085	(0.81)	0.0084	(0.78)	-0.0025	(-0.27)
Down 2 Quarters	0.0033	(0.29)	0.0074	(0.63)	0.0071	(0.59)	0.0012	(0.11)
Down 3 Quarters	0.0056	(0.25)	0.0004	(0.02)	0.0078	(0.34)	-0.0034	(-0.15)
Down 4 Quarters	0.0195	(0.55)	0.0054	(0.15)	0.0234	(0.65)	0.0046	(0.13)
Down 5 Quarters	-0.0351	(-0.58)	-0.0643	(-1.02)	-0.0319	(-0.52)	-0.0531	(-0.85)
Emerging Markets	-0.0079	(-0.67)	-0.0104	(-0.90)	-0.0083	(-0.71)	-0.0110	(-0.90)
Equity Mrkt. Neutral	0.0216	(1.84)	0.0119	(1.03)	0.0203	(1.70)	0.0209	(1.74)
Event Driven	-0.0048	(-0.40)	-0.0044	(-0.38)	-0.0050	(-0.42)	-0.0087	(-0.70)
Fixed Income	0.0055	(0.47)	-0.0088	(-0.77)	0.0041	(0.34)	0.0078	(0.65)
Global Macro	0.0010	(0.08)	0.0012	(0.11)	0.0003	(0.02)	-0.0052	(-0.39)
Long Short Equity	-0.0151	(-1.28)	-0.0249	(-2.15)	-0.0168	(-1.40)	-0.0143	(-1.18)
Managed Futures	0.0143	(1.22)	0.0037	(0.32)	0.0133	(1.12)	0.0112	(0.94)
Adj R^2	0.133		0.0798		0.132		0.0985	
No obs.	359		399		359		359	

Table IV

The Effect of Style Performance
Upon Aggregate Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of aggregate money flows per style. Money flows are the residuals of the cross sectional model estimated in Table II explaining growth rates from style-adjusted performance and fund specific characteristics. We first obtain dollar flows per fund by multiplying the residuals by the total net assets in the previous period. Then we aggregate dollar flows per style and per period. Alternatively, we obtain an aggregate growth rate by dividing aggregate dollar flows by the aggregate total net assets in the previous quarter. The sample consists of 399 style-period observations between 1994Q4 and 2004Q3. The independent variables include three lagged style index returns, a trend variable, eight dummies accounting for the length of upward and downward trends in the style index and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The general hedge fund index is taken as reference category. We estimate our model by pooling all style-period observations. T-statistics are provided in parentheses.

Model explaining style-driven dollar flows
(coefficients expressed in thousands)

	(A)		(B)		(C)		(D)	
Parameters	Coeff.	t-test	Coeff.	t-test.	Coeff.	t-test	Coeff.	t-test
Intercept	-609000	(-6.98)	-156000	(-2.42)	-612000	(-5.65)	-41600	(-0.60)
Style Rank lag 1	32600	(3.65)			38700	(3.15)		
Style Rank lag 2	37600	(4.05)			38800	(3.10)		
Style Rank lag 3	33200	(3.75)			25900	(2.08)		
Style Return lag1			915000	(2.41)	-314000	(-0.63)		
Style Return lag2			849000	(2.09)	-94200	(-0.18)		
Style Return lag3			1410000	(3.69)	433000	(0.84)		
Winning Streak 2							82900	(1.05)
Winning Streak 3							147000	(1.34)
Winning Streak 4							323000	(3.25)
Losing Streak 1							30700	(0.46)
Losing Streak 2							-177000	(-2.28)
Losing Streak 3							-162000	(-1.96)
Losing Streak 4							-220000	(-2.22)
Losing Streak 5							-483000	(-5.78)
Trend	6682	(3.92)	7226	(4.17)	6698	(3.92)	7118	(4.08)
Up 2 Quarters	56700	(0.80)	123000	(1.69)	68000	(0.92)	-3188	(-0.05)
Up 3 Quarters	4081	(0.03)	64400	(0.56)	8931	(0.07)	-12500	(-0.10)
Up 4 Quarters	-133000	(-0.50)	-195000	(-0.68)	-113000	(-0.42)	-169000	(-0.63)
Down 1 Quarter	-19700	(-0.33)	5701	(0.09)	-12700	(-0.19)	-26800	(-0.47)
Down 2 Quarters	-1561	(-0.02)	4806	(0.06)	-18700	(-0.25)	44500	(0.66)
Down 3 Quarters	-68500	(-0.50)	-94400	(-0.68)	-71600	(-0.51)	-69200	(-0.51)
Down 4 Quarters	110000	(0.50)	-25000	(-0.11)	97900	(0.44)	18100	(0.08)
Down 5 Quarters	121000	(0.32)	-82800	(-0.21)	144000	(0.38)	97600	(0.26)
Emerging Markets	-11500	(-0.16)	-20500	(-0.28)	-9726	(-0.13)	-46800	(-0.64)
Equity Mkt.Neutral	4494	(0.06)	-54500	(-0.75)	6170	(0.08)	-9992	(-0.14)
Event Driven	33700	(0.46)	43700	(0.60)	34900	(0.47)	-7950	(-0.11)
Fixed Income	35100	(0.49)	-59900	(-0.83)	35800	(0.49)	65900	(0.91)
Global Macro	34900	(0.47)	47500	(0.64)	35900	(0.48)	-23900	(-0.30)
Long Short Equity	-120000	(-1.66)	-180000	(-2.45)	-121000	(-1.63)	-96600	(-1.33)
Managed Futures	283000	(3.92)	215000	(2.96)	284000	(3.90)	276000	(3.83)
Adj R^2	0.201		0.122		0.196		0.208	
No obs.	359		399		359		359	

5 Style indices and style momentum

The results in the previous section indicate that investors on aggregate direct their money towards those styles for which the index displayed higher returns compared to other indices. Conversely, investors on aggregate pulled out their money from those styles with corresponding index returns below other indices. This suggests not only that investors pay attention to the style indices, but apparently they also expect continuation in the performance of the index. This section explores whether there is any evidence of persistence in returns across style indices.

The question of style momentum is not trivial. Studies on persistence have identified momentum in individual hedge funds both in raw returns and style-adjusted returns. But, is momentum related to specific funds or is it also a property of a specific investment category? Is persistence related to the skills of an individual manager, or to the success of a trading style under specific market circumstances? As with individual funds, differences in returns across style indices might be associated to risk differentials. Table I, Panel A, shows for example that the indices *Dedicated Short Bias* and *Emerging Markets* are the most volatile in terms of standard deviation of historical quarterly returns. Another way to look at the riskiness of a given style index relative to other indices is by ranking the nine Tremont indices in each period in terms of returns, and then computing the frequency of rank position for each index. Table V reports the frequencies for both monthly rankings (Panel A) and quarterly rankings (Panel B) over the period January 1994-December 2004. The rank 9 corresponds to the index with the highest return in a given period. For example, the index *Dedicated Short Bias* offered the highest returns across styles in 24.24% of the 132 months, while it displayed the worst returns (rank 1) 39.39% of the time. Also the indices *Emerging Markets* and *Managed Futures* alternate very often between the extreme rank positions. All other indices are less volatile and rank most often in the middle positions. We observe similar patterns with quarterly rankings (Panel B).

In order to obtain a first indication of persistence in returns of style indices, we analyze the likelihood that the winning styles remain the winners in the subsequent period. Figure 2, shows a contingency table of quarterly index performance. In each quarter we compare the rank position of any index with its rank in the subsequent quarter. The style indices ranked in the top position (rank 9) have 28% of probabilities to remain in the top rank, but also 28% of probabilities to revert to the bottom rank. Similarly, the styles in the bottom rank are very likely to alternate between the bottom rank and the top rank.[15]

[15] A pertinent question is to what extent these figures are the result of a survivorship bias affecting style indices performance? Arguably, the funds used to construct the indices of these highly volatile categories

Table V

Rank Frequencies per Style Index

In each period we rank the nine Tremont indices in terms of returns. Then we compute the frequency of rank position for each index. The table reports the frequencies for both monthly rankings (Panel A) and quarterly rankings (Panel B) over the period January 1994-December 2004. The rank 9 corresponds to the index with the highest return in a given period.

Panel A: Rank frequency (%) at monthly horizons

Rank Position		Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity	Managed Futures
Top	9	2.27	24.24	25.00	5.30	3.79	0.00	9.09	13.64	16.67
	8	12.88	8.33	15.15	3.79	9.85	6.82	18.94	14.39	9.85
	7	15.15	2.27	6.82	13.64	15.15	11.36	14.39	13.64	7.58
	6	13.64	4.55	7.58	14.39	25.00	12.12	12.88	5.30	4.55
	5	15.15	2.27	4.55	17.42	21.97	14.39	5.30	12.12	6.82
	4	14.39	3.03	3.79	19.70	11.36	20.45	10.61	9.09	7.58
	3	15.91	3.03	2.27	13.64	7.58	23.48	11.36	9.09	13.64
	2	7.58	12.88	12.12	10.61	4.55	10.61	10.61	15.91	15.15
Bottom	1	3.03	39.39	22.73	1.52	0.76	0.76	6.82	6.82	18.18

Panel B: Rank frequency (%) at quarterly horizons

Rank Position		Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity	Managed Futures
Top	9	6.82	34.09	31.82	0.00	2.27	0.00	6.82	6.82	11.36
	8	4.55	4.55	13.64	11.36	4.55	4.55	20.45	18.18	18.18
	7	11.36	0.00	2.27	4.55	31.82	9.09	25.00	11.36	4.55
	6	9.09	0.00	9.09	25.00	25.00	9.09	11.36	6.82	4.55
	5	20.45	2.27	0.00	15.91	15.91	15.91	6.82	13.64	9.09
	4	27.27	0.00	4.55	18.18	6.82	18.18	9.09	9.09	6.82
	3	11.36	4.55	2.27	13.64	6.82	34.09	9.09	13.64	4.55
	2	9.09	6.82	11.36	11.36	4.55	9.09	2.27	15.91	29.55
Bottom	1	0.00	47.73	25.00	0.00	2.27	0.00	9.09	4.55	11.36

Although the probabilities for the extreme ranks are to a large extent driven by the three most volatile style categories mentioned above (namely *Dedicated Short Bias*, *Emerging Markets* and *Managed Futures*), we also observe that the ranks 6, 7 and 8 have large probabilities of nearly 20% to remain in one of the top three ranks in the subsequent quarter, while the ranks 2, 3 and 4 are more likely to remain in one of the bottom three ranks.[16]

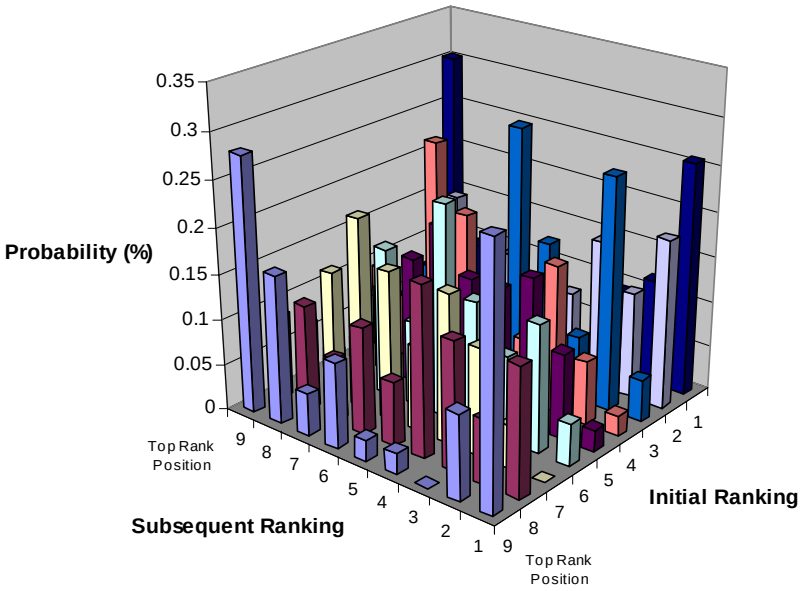
are more likely to liquidate in case of extremely bad outcomes. By the same token, they are likely to exhibit very high returns conditional upon survival (see Fung and Hsieh [1999]).

[16] At monthly horizons, the style indices ranked in the top position (rank 9) have a probability of 25% to remain in the top rank. However there is a 12% probability that it reverts to the bottom rank. Similarly, the style indices in the bottom rank, have a probability of nearly 30% to remain the losers. We found some evidence of persistence at monthly horizons in style index returns. The top rank provides an average monthly return of 1.3% compared to nearly -0.4% of the bottom rank. The difference of 1.7% is statistically significant at the 1% level. However, when we repeat this analysis by splitting the sample period in two halves, we only find statistically significant evidence of persistence in the first halve, from January 1994 till April 1999.

Figure 2

Contingency Table of Quarterly Style Index Performance

The nine Tremont indices are ranked each period based on the net returns at the end of the period. We compare the initial rank position of any index with its rank in the subsequent month. The bar in cell *(i,j)* represents the conditional probability of achieving a subsequent rank position *j* given an initial rank position *i*.



The previous analysis indicates that some style indices tend to persist in the two extreme ranks. However, this does not necessarily imply that the winning style indices in one period offer on average higher returns than other indices in the subsequent period, given the high turnover rates of indices across ranks. Therefore, we also calculate the average returns per rank in the period following the ranking. The statistical tests presented in Table VI for the entire sample period and the two half periods do not support the idea of performance persistence at the style level. In fact, the top rank underperforms most of other above-median ranks, as also shown in Figure 3. The difference between the top and bottom portfolios is of about 0.4% per quarter, statistically insignificant.

Table VII presents additional persistence tests by separating style indices between winners and losers, using different thresholds to define winners and losers. We follow the performance of each style over the four subsequent evaluation periods after ranking. For example, Panel B shows the results when we consider the style indices in the two top ranks as the winning styles. In the ranking period, the portfolio of winning styles significantly outperforms the portfolio of losing styles by 8.97%. In the subsequent quarter, however, we find no significant differences between both portfolios. For further

evaluation periods, the difference becomes in some cases even negative. We observe similar patterns in the remaining panels where we use other thresholds to define the winning portfolio.

Table VI

Analysis of Persistence in Quarterly Style Index Returns

In each quarter between 1994Q1 and 2004Q4 we rank the nine Tremont indices in terms of absolute returns. The rank 9 corresponds to the index with the highest return in a given period. The table reports average returns per rank in the period following the ranking.

		Sample period (Jan 1994 – Dec2004)		First half period 1994 Q1- 1999Q1		Second half period 1999 Q2- 2004 Q3	
		Average return	t-test	Average return	t-test	Average return	t-test
Top rank	9	0.0223	(1.55)	0.0245	(1.14)	0.0202	(1.02)
	8	0.0228	(2.75)	0.0262	(2.01)	0.0195	(1.84)
	7	0.0368	(5.94)	0.0460	(4.42)	0.0280	(4.23)
	6	0.0173	(3.05)	0.0103	(1.15)	0.0240	(3.45)
	5	0.0247	(3.16)	0.0192	(2.15)	0.0299	(2.34)
	4	0.0345	(5.51)	0.0449	(4.83)	0.0246	(3.05)
	3	0.0135	(1.88)	0.0125	(0.96)	0.0144	(2.10)
	2	0.0134	(1.33)	0.0001	(0.00)	0.0261	(1.68)
Bottom rank	1	0.0180	(1.12)	0.0205	(0.77)	0.0156	(0.82)
Top minus bottom		0.0043	(0.17)	0.0040	(0.10)	0.0046	(0.14)

Figure 3

Analysis of Quarterly Persistence in Style Index Performance

In each quarter between 1994Q1 and 2004Q4 we rank the nine Tremont indices in terms of absolute returns. The rank 9 corresponds to the index with the highest return in a given period. The figure shows average returns per rank in the period following the ranking.

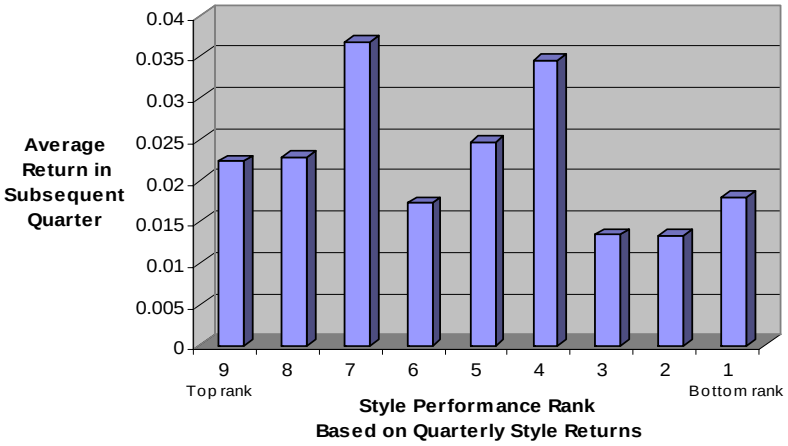


Table VII

Persistence Analysis of Winners and Losers in Quarterly Style Index Returns

In each quarter between 1994Q4 and 2004Q3 we rank the nine Tremont indices in terms of absolute returns. The rank 9 corresponds to the index with the highest return in a given period. Then we separate style indices between winners and losers, using different thresholds to define winners and losers. The table reports average returns over the four subsequent evaluation periods.

Momentum in Quarterly Returns

Panel A: Only the top rank is the winner

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.1104	0.0281	-0.0004	0.0360	0.0201
Losers	0.0116	0.0227	0.0259	0.0209	0.0242
Difference	0.0988	0.0054	-0.0263	0.0151	-0.0041
t-test	(10.36)	(0.33)	(-1.83)	(1.07)	(-0.28)

Panel B: The two top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0923	0.0261	0.0106	0.0321	0.0155
Losers	0.0027	0.0225	0.0266	0.0199	0.0261
Difference	0.0897	0.0036	-0.0159	0.0122	-0.0105
t-test	(10.53)	(0.36)	(-1.44)	(1.10)	(-0.90)

Panel C: The three top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0778	0.0304	0.0203	0.0307	0.0204
Losers	-0.0051	0.0197	0.0244	0.0186	0.0254
Difference	0.0829	0.0107	-0.0041	0.0121	-0.0050
t-test	(11.41)	(1.32)	(-0.43)	(1.44)	(-0.57)

Panel D: the four top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0667	0.0268	0.0229	0.0301	0.0232
Losers	-0.0127	0.0205	0.0231	0.0166	0.0242
Difference	0.0794	0.0063	-0.0002	0.0135	-0.0010
t-test	(13.16)	(0.79)	(-0.03)	(1.56)	(-0.10)

Panel D: the five top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0583	0.0263	0.0244	0.0294	0.0218
Losers	-0.0221	0.0195	0.0212	0.0141	0.0261
Difference	0.0804	0.0068	0.0032	0.0153	-0.0044
t-test	(14.88)	(0.96)	(0.41)	(1.78)	(-0.46)

In conclusion, our tests reject the hypothesis of performance persistence of style indices at quarterly horizons. Past relative performance appears to convey no information about future performance. This is a very puzzling result, if we consider the evidence presented in Section 4 that investors follow momentum strategies at the style level, powerfully attracted by the best performing categories. Admittedly, the actual investors' allocation

might not be entirely equivalent to the investment strategy analyzed in this section, which is strictly based on separating styles between winners and losers. Therefore, the next Section analyzes the effectiveness of investors' allocations and the possibility that they reflect informed choices.

6 Testing smart timing

The analysis in Section 4 showed that aggregate money flows are sensitive to the performance of styles in the previous one to three quarters. Ceteris paribus, investors direct their inflows to the styles with higher returns in the past. Conversely, they withdraw their money in general from those styles with lower returns in the previous quarter. These patterns suggest that investors indeed attempt to time the styles based on index performance information. This seems inconsistent, however, with the results of last section, which indicate that past relative performance of style indices is unrelated to future performance. The present section relates aggregate money flows to the subsequent performance of style indices. Specifically, we analyze whether investors succeed in their timing attempt and shift their money towards those styles with higher returns in the future. To this effect, in each quarter we rank the style indices in terms of their corresponding aggregate money flows at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. Finally we obtain the time series average returns of each portfolio over the 40 quarters. We compute the cash flow-weighted returns using both aggregate growth rates and aggregate dollar flows that occur in the ranking period. By using growth rates, we reduce the bias towards styles that have more numerous and larger funds. We can interpret this measure as a cash-flow-weighted return per unit of total net assets. Instead, by using dollar flows we reduce the bias towards styles for which the number of funds in our sample is not representative enough, namely the C*onvertible Arbitrage* and *Dedicated Short Bias* strategies.

Table VIII shows the results when we use the residual aggregate growth rates as the ranking variable. In the ranking period, the portfolio with positive flows significantly outperforms the portfolio with negative money flows by 2.48% in terms of cash-flow weighted returns (Panel A). In the two lagged quarters, the difference is even larger, of about 3.70% and 3.35% respectively. This is again an indication that investors select styles based on past indices performance, consistent with our previous results in Tables III and IV.

Table VIII

Investors' Returns from Style Allocation

In each quarter we rank the style indices in terms of their corresponding aggregate residual growth rates at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Aggregate residual growth rates							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0363	0.0390	0.0302	0.0210	0.0163	0.0239	0.0200
Styles with net negative flows	0.0028	0.0021	0.0054	0.0221	0.0336	0.0212	0.0287
Difference	0.0335	0.0370	0.0248	-0.0011	-0.0173	0.0028	-0.0087
T-test	(3.41)	(3.40)	(2.61)	(-0.13)	(-1.71)	(0.29)	(-0.85)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0345	0.0367	0.0296	0.0259	0.0196	0.0243	0.0185
Styles with net negative flows	0.0062	0.0061	0.0129	0.0206	0.0276	0.0238	0.0307
Difference	0.0283	0.0307	0.0166	0.0053	-0.0079	0.0005	-0.0122
T-test	(3.70)	(3.71)	(3.06)	(0.70)	(-0.94)	(0.09)	(-1.43)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0018	0.0023	0.0006	-0.0049	-0.0034	-0.0004	0.0015
T-test	(0.43)	(0.56)	(0.17)	(-1.13)	(-0.99)	(-0.09)	(0.45)
Styles with net negative flows	-0.0034	-0.0040	-0.0076	0.0015	0.0060	-0.0026	-0.0020
T-test	(-1.04)	(-0.97)	(-1.84)	(0.46)	(1.51)	(-0.47)	(-0.67)

Table IX reports similar patterns when we use aggregate residual dollar flows as the ranking variable. Moreover, in the second lagged quarter, the cash flow weighted return significantly outperforms the equally weighted return by 1.08% for the portfolio with positive flows (Panel C). Thus, inflows are not equally distributed across styles in each portfolio. Inflows are more heavily placed in those styles with the highest index returns in the previous quarters.

Aggregate money flows appear to have a sorting capacity of contemporaneous and lagged index performance, a result that parallels the one obtained for individual funds (see Baquero and Verbeek [2006a]).[17] However, money flows fail to discriminate future

[17] Apparently, contemporaneous index performance has also an impact on aggregate money flows, although the effect is substantially reduced compared to the one of lagged quarters. Presumably, along a quarter,

index performance. We do not find significant differences between the two portfolios over the four subsequent quarters. In fact, in the fourth quarter, styles with negative flows increasingly outperform those with positive flows. The results from Table VIII are depicted in Figure 4. In sum, we find evidence that investors attempt to time the styles, but apparently aggregate flows are not smart.

In Section 4 we showed that lagged style ranks and individual style effects explain nearly 13% of the cross-sectional variation of aggregate residual growth rates and nearly 20% of aggregate residual dollar flows (specification in Panel A, Table III). Therefore, we can obtain an estimate of the component of aggregate money flows explained by the models reported in Tables III and IV, which can be referred to as *style-driven flows*, in order to have a more accurate picture of the style-timing attempts of investors. Table A5 in the appendix reports our results when we use style-driven growth rates. In the two lagged quarters, the differences between the portfolios with positive and negative money flows are now 8.55% and 5.95% respectively in terms of cash-flow weighted returns, which are substantially larger compared to our previous results using residual growth rates (Table VIII). Table A6 reports similar results with style-driven dollar flows.

The fact that investors are unable to time the styles, suggests that investors tend to misread style index performance information. It also suggests that style indices may not be representative enough of broad investment categories, or that each style is such a heterogeneous class that it makes little sense to treat each style as a category for benchmarking purposes. Alternatively, it could also be that the coordinated shift of capital supply to some categories drives itself the performance of those categories downwards. Hedge fund strategies may not be easily scalable and superior investment opportunities to allocate a massive money inflow may become rapidly scarce. Still, the question then is why sophisticated investors fail to learn and anticipate such effects.

Our results also reveal that investors' style allocation is not exactly equivalent to the chasing-the-winning-style strategy analyzed in Section 5. Both strategies show little correlation. We find an average Spearman-rank correlation coefficient over time of nearly 30% (not reported). Investors tend to allocate higher amounts of money to styles with higher returns, but not necessarily the styles with the highest returns. On the other hand, very risky strategies are also favored by clients. These strategies often shift from very high returns to very low returns and vice versa. Investors place large amounts of money into these strategies even when they have experienced low returns, presumably in the expectation of a reversal.

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investors observe monthly index returns, which may have an effect on money flows by the end of the quarter. However, given the typical redemption restrictions imposed by most hedge funds, it is unlikely that investors profit from contemporaneous information on index returns.

Figure 4

Investors' Returns from Style Allocation

In each quarter we rank the style indices in terms of their corresponding aggregate residual growth rates at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The figure depicts the time series average returns of each portfolio over the 40 quarters.

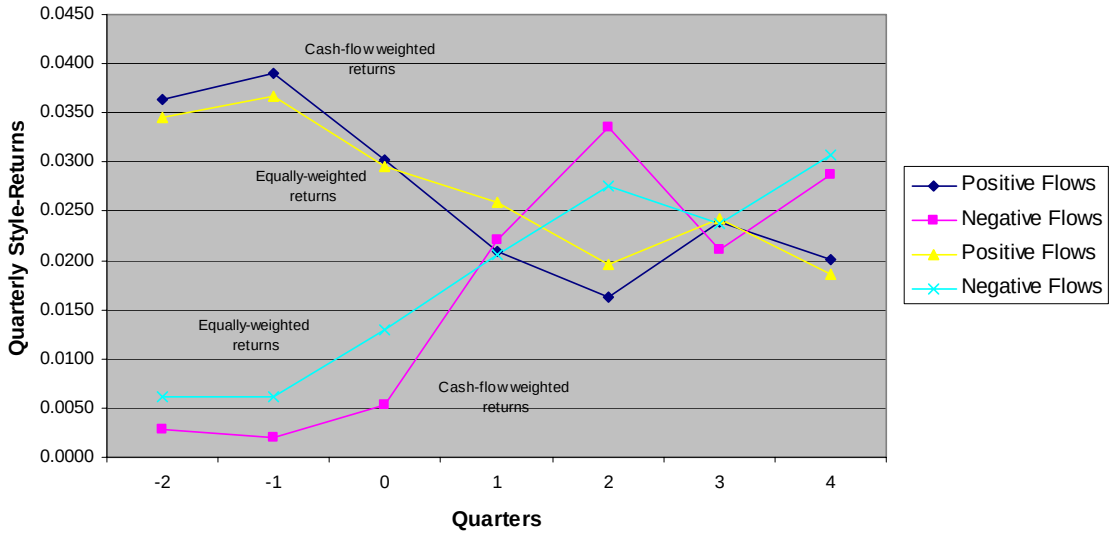

Table IX

Investors' Returns from Style Allocation

In each quarter we rank the style indices in terms of their corresponding aggregate residual dollar flows at the end of the period. Next, we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Aggregate residual dollar flows							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0453	0.0468	0.0322	0.0268	0.0235	0.0224	0.0205
Styles with net negative flows	0.0081	0.0102	0.0192	0.0269	0.0320	0.0306	0.0385
Difference	0.0372	0.0366	0.0130	-0.0002	-0.0085	-0.0082	-0.0180
T-test	(3.76)	(4.60)	(2.01)	(-0.02)	(-1.03)	(-1.05)	(-2.22)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0345	0.0367	0.0296	0.0259	0.0196	0.0243	0.0185
Styles with net negative flows	0.0062	0.0061	0.0129	0.0206	0.0276	0.0238	0.0307
Difference	0.0283	0.0307	0.0166	0.0053	-0.0079	0.0005	-0.0122
T-test	(3.70)	(3.71)	(3.06)	(0.70)	(-0.94)	(0.09)	(-1.43)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0108	0.0100	0.0026	0.0009	0.0039	-0.0019	0.0020
T-test	(2.10)	(1.70)	(0.70)	(0.22)	(1.03)	(-0.36)	(0.48)
Styles with net negative flows	0.0019	0.0041	0.0062	0.0063	0.0044	0.0069	0.0078
T-test	(0.42)	(1.25)	(1.40)	(1.59)	(0.96)	(1.77)	(2.20)

7 Concluding Remarks

The results of this study indicate that investors learn at the style-level and invest following a momentum strategy, whereby they chase the winning styles. We find a statistically significant relation between aggregate residual money flows and the relative performance of style indices over the previous one to three quarters. Aggregate money flows exhibit a sorting ability of past style index performance. However, aggregate money flows are unrelated to future style performance. There are no significant differences in subsequent performance between those styles favored by investors and those less favored. Further, we do not find evidence that past style index performance contains useful information of future performance. These two facts together suggest that style investing is the result of a common sentiment factor and reflects extrapolative expectations, consistent with the hypothesis of Barberis and Shleifer [2003]. Previous studies have shown that also within-style allocations at the individual fund level are inefficient (e.g. Baquero and Verbeek [2006a]). Overall, these results raise serious concerns about investors' ability to make the right allocation choices.

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Appendix

Table A1

Aggregate Cash Flows and Total Net Assets from a Sample of Hedge Funds from TASS Database

This table gives the total number of hedge funds in the sample per quarter, aggregate cash flows, total net assets under management and average return. The sample consists of 1543 open-end hedge funds taken from TASS database, with a minimum of 6 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included. The sample period has 40 quarters from 1994Q4 till 2004Q3. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to TNA of previous period.

	Number of funds	Aggregate Cash Flows (million dollars)	Cash flows (growth rate)	Aggregate TNA (million dollars)	Average Return
1994 Q4	231	-437.44	-0.0235	17861.15	-0.0077
1995 Q1	258	-1312.14	-0.0646	19387.67	0.0524
1995 Q2	279	-461.56	-0.0228	20469.12	0.0370
1995 Q3	315	-317.83	-0.0146	22972.14	0.0459
1995 Q4	326	-757.99	-0.0327	23215.81	0.0345
1996 Q1	348	148.85	0.0050	30969.63	0.0244
1996 Q2	360	-334.21	-0.0107	33047.34	0.0596
1996 Q3	364	377.79	0.0112	34275.64	0.0164
1996 Q4	371	945.09	0.0260	40431.19	0.0603
1997 Q1	379	2277.90	0.0561	45255.20	0.0427
1997 Q2	392	301.99	0.0066	48434.29	0.0467
1997 Q3	414	2353.93	0.0471	56745.53	0.0742
1997 Q4	438	675.00	0.0115	59948.61	-0.0136
1998 Q1	470	1821.63	0.0295	66989.86	0.0484
1998 Q2	482	1107.31	0.0167	68556.61	-0.0240
1998 Q3	496	-268.07	-0.0041	60234.29	-0.0502
1998 Q4	528	-3822.72	-0.0615	56650.24	0.0518
1999 Q1	571	-2845.61	-0.0490	55262.50	0.0324
1999 Q2	582	-850.49	-0.0152	58979.19	0.0832
1999 Q3	598	-1289.20	-0.0219	56682.70	-0.0006
1999 Q4	597	-703.00	-0.0124	63413.15	0.1177
2000 Q1	626	670.00	0.0101	69948.90	0.0607
2000 Q2	629	-2299.42	-0.0336	63643.12	-0.0139
2000 Q3	658	697.77	0.0108	67016.20	0.0185
2000 Q4	667	734.74	0.0109	68463.32	-0.0020
2001 Q1	670	3382.16	0.0456	78678.59	0.0086
2001 Q2	697	3380.75	0.0403	89049.14	0.0257
2001 Q3	699	3145.77	0.0355	89959.58	-0.0250
2001 Q4	702	-5713.63	-0.0574	97069.95	0.0482
2002 Q1	702	1533.24	0.0157	100359.61	0.0184
2002 Q2	700	2279.75	0.0222	105192.95	0.0057
2002 Q3	702	67.69	0.0006	104609.51	-0.0212
2002 Q4	697	-1099.04	-0.0104	106726.81	0.0219
2003 Q1	685	2431.55	0.0255	99383.00	0.0116
2003 Q2	687	5628.85	0.0560	112169.77	0.0775
2003 Q3	703	6970.84	0.0607	124438.64	0.0376
2003 Q4	711	6722.30	0.0539	137685.21	0.0541
2004 Q1	703	16056.57	0.1207	154496.43	0.0409
2004 Q2	712	10330.84	0.0659	163689.45	-0.0244
2004 Q3	692	2730.60	0.0170	164632.56	0.0090

Table A2

Cross-Sectional Characteristics of the Hedge Fund Sample

This table presents summary statistics on cross-sectional characteristics of our sample of 1543 hedge funds for the period 1994Q4 till 2004Q3. Cash flows are the change in total net assets between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the US Treasury bill taken as the minimum investor's target. Offshore is a dummy variable with value one for non U.S. domiciled funds. Incentive fee is a percentage of profits above a hurdle rate that is given as a reward to managers. Management fee is a percentage of the fund's net assets under management that is paid annually to managers for administering a fund. Personal capital is a dummy variable indicating that the managers invests from her own wealth in the fund. We include 10 dummies for investment styles defined on the basis of the CSFB/Tremont indices.

Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0287	0.2734	-0.9107	4.3656
Cash Flows>0 (10876 obs)	0.1639	0.3052	0.0001	4.3656
Cash Flows<0 (10367 obs)	-0.1115	0.1444	-0.9107	-0.0001
Cash Flows=0 (598 obs)				
Cash Flows (dollars)	2484343	6.80E+07	-7.23E+09	1.12E+09
ln(TNA)	17.1746	1.8491	8.1050	23.2959
ln(AGE)	4.0070	0.6189	2.8904	5.8171
Quarterly Returns	0.0255	0.1175	-0.9763	1.7449
Historical St.Dev.	0.0513	0.0407	0.0004	0.8318
Semi Deviation	0.0299	0.0245	0	0.3326
Upside Potential	0.0236	0.0169	0.0002	0.2797
Downside-Upside Pot. Ratio	1.2862	0.8600	0	19.2076
Offshore	0.6236	0.4845	0	1
Incentive Fee	18.4599	5.8253	0	50
Management Fees	1.4632	0.8832	0	8
Personal Capital	0.6197	0.4855	0	1
Leverage	0.7579	0.4283	0	1
Convertible Arbitrage	0.0525	0.2231	0	1
Dedicated Short Bias	0.0160	0.1256	0	1
Emerging Markets	0.1036	0.3047	0	1
Equity Market Neutral	0.0463	0.2102	0	1
Event Driven	0.1222	0.3275	0	1
Fixed Income Arbitrage.	0.0490	0.2159	0	1
Global Macro	0.0691	0.2536	0	1
Long/Short Equity	0.3468	0.4760	0	1
Managed Futures	0.1576	0.3644	0	1
Hedge Fund Index	0.0368	0.1883	0	1

Table A3

Summary of Number of Funds per Style and per Period

This table gives the total number of hedge funds in the sample per quarter and per style category. The sample consists of 1543 open-end hedge funds taken from TASS database, with a minimum of 6 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included. The sample period has 40 quarters from 1994Q4 till 2004Q3. This results in a total of 21841 fund-period observations.

Style	Conv. Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitr.	Global Macro	Long/ Short Equity	Managed Futures	Other	**Total**
1994Q4	9	3	17	5	25	7	24	74	63	4	**231**
1995Q1	11	3	18	6	24	9	29	84	69	5	**258**
1995Q2	10	3	19	7	27	10	32	89	75	7	**279**
1995Q3	10	5	27	8	27	12	35	96	88	7	**315**
1995Q4	12	5	26	8	31	13	34	100	89	8	**326**
1996Q1	15	5	29	9	34	19	36	97	94	10	**348**
1996Q2	15	5	33	8	38	22	35	104	90	10	**360**
1996Q3	12	5	36	9	38	20	37	105	91	11	**364**
1996Q4	14	5	35	10	41	20	36	105	92	13	**371**
1997Q1	16	5	36	11	46	20	38	108	87	12	**379**
1997Q2	16	5	39	11	47	20	39	111	93	11	**392**
1997Q3	17	5	38	13	52	22	38	125	90	14	**414**
1997Q4	18	5	45	13	55	25	40	134	89	14	**438**
1998Q1	20	5	50	14	60	25	41	152	89	14	**470**
1998Q2	20	6	50	15	64	21	39	161	92	14	**482**
1998Q3	17	9	46	15	67	22	41	176	89	14	**496**
1998Q4	19	11	52	18	68	22	42	186	96	14	**528**
1999Q1	19	12	59	22	79	22	49	194	99	16	**571**
1999Q2	22	11	65	25	72	24	50	193	104	16	**582**
1999Q3	24	11	65	26	73	28	49	200	106	16	**598**
1999Q4	28	11	66	23	72	31	50	202	97	17	**597**
2000Q1	32	12	70	25	74	35	49	216	96	17	**626**
2000Q2	34	13	74	28	73	34	46	219	91	17	**629**
2000Q3	33	13	76	31	77	38	39	242	91	18	**658**
2000Q4	37	13	82	31	83	35	34	246	85	21	**667**
2001Q1	33	12	74	38	83	35	34	249	89	23	**670**
2001Q2	34	12	78	43	88	36	33	256	90	27	**697**
2001Q3	38	11	79	44	89	36	31	252	91	28	**699**
2001Q4	40	11	78	43	90	33	32	262	85	28	**702**
2002Q1	43	11	78	38	88	32	31	262	88	31	**702**
2002Q2	48	10	79	36	89	33	29	261	84	31	**700**
2002Q3	46	10	80	35	88	35	31	266	80	31	**702**
2002Q4	45	12	77	39	89	32	34	261	76	32	**697**
2003Q1	44	12	73	40	86	33	33	253	77	34	**685**
2003Q2	45	12	70	40	88	33	33	257	74	35	**687**
2003Q3	47	12	69	49	86	37	35	257	74	37	**703**
2003Q4	51	12	69	45	89	36	37	258	76	38	**711**
2004Q1	50	11	69	44	92	35	39	255	72	36	**703**
2004Q2	54	8	68	46	90	35	46	258	70	37	**712**
2004Q3	49	8	68	41	87	34	49	248	72	36	**692**
TOTAL	**1147**	**350**	**2262**	**1012**	**2669**	**1071**	**1509**	**7574**	**3443**	**804**	**21841**

Table A4

Summary Statistics of Aggregate Flows and Measures of Style Performance

This table presents summary statistics of aggregate money flows and different measures of performance at the style level. Our dataset covers 40 quarters from 1994Q4 to 2004Q3. We aggregate, per style and per period, residual growth rates and residual dollar flows obtained from the model in Table III. One significant outlier corresponding to the Convertible Arbitrage strategy in 2001Q4 is excluded. This results in 359 style-period observations when the 9 style indices are considered and 399 observations when the general Hedge Fund Index is also included. The style rank is obtained by ranking all 9 indices in each period in terms of returns. The winner/loser dummy takes value 1 if the style is ranked among the top best performing styles. A set of 9 dummies accounts for the length of winning and losing streaks. For instance, the dummy *Winning Streak 2* takes value 1 if the style index is a winner over 2 consecutive quarters. The dummy *Winning Streak 4* accounts for winning streaks of four quarters length or more. Similarly, *Losing Streak 5* accounts for losing streaks of five quarters or more. A set of 9 dummies accounts for the length of upward and downward trends in style index returns. Finally, the 10 dummies for investment styles are defined on the basis of the CSFB/Tremont indices.

Variable	Observ.	Mean	Std. Dev.	Min	Max
Aggregate Residual Growth Rates	399	0.0149	0.0648	-0.2673	0.2345
Aggregate Residual Dollar Flows	399	83400000	421000000	-2.11E+09	1.81E+09
Trend Variable	399	20.4787	11.5645	1	40
Quarterly Style Index Return	399	0.0233	0.0612	-0.2867	0.3066
Quarterly Style Rank	359	4.4962	2.8785	1	9
Winner/Loser Dummy	359	0.4429	0.4974	0	1
Winning Streak 1	399	0.2105	0.4082	0	1
Winning Streak 2	359	0.0977	0.2973	0	1
Winning Streak 3	359	0.0351	0.1842	0	1
Winning Streak 4	359	0.0551	0.2285	0	1
Losing Streak 1	359	0.2130	0.4100	0	1
Losing Streak 2	359	0.0977	0.2973	0	1
Losing Streak 3	359	0.0677	0.2515	0	1
Losing Streak 4	359	0.0451	0.2078	0	1
Losing Streak 5	359	0.0777	0.2680	0	1
Up 1 Quarters	399	0.3208	0.4674	0	1
Up 2 Quarters	399	0.1303	0.3371	0	1
Up 3 Quarters	399	0.0351	0.1842	0	1
Up 4 Quarters	399	0.0050	0.0707	0	1
Down 1 Quarter	399	0.3358	0.4729	0	1
Down 2 Quarters	399	0.1404	0.3478	0	1
Down 3 Quarters	399	0.0226	0.1487	0	1
Down 4 Quarters	399	0.0075	0.0865	0	1
Down 5 Quarters	399	0.0025	0.0501	0	1
Convertible Arbitrage	399	0.0977	0.2973	0	1
Dedicated Short Bias	399	0.1003	0.3007	0	1
Emerging Markets	399	0.1003	0.3007	0	1
Equity Market Neutral	399	0.1003	0.3007	0	1
Event Driven	399	0.1003	0.3007	0	1
Fixed Income Arbitrage	399	0.1003	0.3007	0	1
Global Macro	399	0.1003	0.3007	0	1
Long/Short Equity	399	0.1003	0.3007	0	1
Managed Futures	399	0.1003	0.3007	0	1
General Hedge fund index	399	0.1003	0.3007	0	1

Table A5

Investors' Returns From Style Allocation

In each quarter we rank the style indices in terms of style-driven growth rates at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Style-Driven Growth Rates							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0434	0.0535	0.0293	0.0239	0.0213	0.0191	0.0209
Styles with net negative flows	-0.0161	-0.0320	0.0072	0.0085	0.0171	0.0352	0.0274
Difference	0.0595	0.0855	0.0221	0.0154	0.0041	-0.0161	-0.0066
T-test	(4.98)	(8.16)	(2.08)	(1.29)	(0.36)	(-1.36)	(-0.50)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0368	0.0444	0.0276	0.0261	0.0261	0.0207	0.0228
Styles with net negative flows	-0.0080	-0.0224	0.0075	0.0146	0.0155	0.0326	0.0265
Difference	0.0448	0.0668	0.0200	0.0115	0.0106	-0.0119	-0.0038
T-test	(4.24)	(7.71)	(2.29)	(1.31)	(1.10)	(-1.21)	(-0.39)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0066	0.0091	0.0018	-0.0022	-0.0049	-0.0016	-0.0019
T-test	(2.59)	(4.04)	(0.84)	(-0.80)	(-1.92)	(-0.76)	(-0.77)
Styles with net negative flows	-0.0081	-0.0096	-0.0003	-0.0061	0.0016	0.0026	0.0009
T-test	(-2.62)	(-3.54)	(-0.08)	(-1.61)	(0.33)	(0.79)	(0.24)

Table A6

Investors' Returns From Style Allocation

In each quarter we rank the style indices in terms of style-driven dollar flows at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Style-Driven Dollar Flows							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0513	0.0439	0.0273	0.0225	0.0164	0.0131	0.0194
Styles with net negative flows	-0.0224	-0.0176	0.0051	0.0128	0.0236	0.0285	0.0302
Difference	0.0737	0.0615	0.0222	0.0096	-0.0073	-0.0153	-0.0108
T-test	(6.34)	(5.47)	(2.06)	(0.81)	(-0.67)	(-1.27)	(-0.90)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0409	0.0395	0.0317	0.0260	0.0220	0.0207	0.0213
Styles with net negative flows	-0.0092	-0.0058	0.0053	0.0242	0.0244	0.0244	0.0320
Difference	0.0501	0.0452	0.0264	0.0017	-0.0025	-0.0037	-0.0107
T-test	(5.25)	(6.12)	(3.20)	(0.19)	(-0.28)	(-0.42)	(-1.21)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0104	0.0044	-0.0044	-0.0035	-0.0056	-0.0075	-0.0019
T-test	(4.32)	(1.45)	(-1.34)	(-1.02)	(-2.11)	(-1.93)	(-0.72)
Styles with net negative flows	-0.0132	-0.0119	-0.0002	-0.0114	-0.0008	0.0041	-0.0018
T-test	(-2.98)	(-2.47)	(-0.04)	(-2.55)	(-0.18)	(1.05)	(-0.43)