

# The Consistency of Self-Declared Hedge Fund Styles – A Return-Based Analysis with Self-Organizing Maps

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While hedge funds have common features, they remain an extremely diverse asset class. Despite this diversity, a consistent classification system is important for numerous purposes such as portfolio construction, performance attribution as well as risk management. This topic is also connected to the financial stability debate, which has recently dealt intensively with the issue of hedge funds. Diversified (fund) portfolios with an appropriate risk monitoring system in place will e.g. enhance risk-sharing among financial market participants. As fund self-declaration is prone to strategic misclassification, return-based taxonomies grouping funds along similarities in realized returns can be used to avoid this pitfall. In this paper we use Self-Organizing Maps (SOM) to find homogeneous groups of hedge funds based on similar (return) characteristics. Based on this technique, we can identify nine hedge fund classes. Whereas managed futures, sector financial and short-sell hedge funds are largely consistent in their self-declared strategies, we detect a number of declared hedge fund styles displaying no or very limited return similarities. Especially the so-called “equity hedge” style encompasses too many different substyles with different return characteristics. Another important aspect that our paper addresses is the tendency of fund managers to perform undisclosed changes of their trading style or to strategically misdeclare their funds. Our results show that so called “style creep” is an issue in the hedge fund business, with funds which misclassified themselves once being very likely to change their trading style again.

## 1 Introduction

Despite the relatively limited share of hedge fund assets in overall financial market assets in industrialized countries, the significant rise both in the size and the number of hedge funds in operation as well as the increased interest of institutional investors in this asset class has shifted hedge funds to the center of financial market stability debate. However, there is no simple answer to the question whether hedge funds enhance or endanger financial market stability. It can be argued that hedge funds add liquidity to some inherently illiquid market segments and help achieve efficient risk-sharing among participants in financial markets. Furthermore, they potentially expand the investment possibility set and provide diversification benefits when added to

portfolios of traditional stock and/or bond investments. The extensive use of leverage by hedge funds, however, creates liquidity risk for the funds themselves. This may put strains on market segments hedge funds are particularly involved in and may lead to spillover effects that affect other financial intermediaries.<sup>2</sup> The experience of the Long Term Capital Management (LTCM) crisis in 1998 is a case in point. When the Russian Federation announced a debt moratorium, a global shift in demand towards safe and liquid assets initiated a widening in risk spreads. Together with a change in correlations between markets, i.e. simultaneous slumps in hitherto uncorrelated market segments, this development inflicted huge losses on LTCM, bringing the fund to the verge of bankruptcy.<sup>3</sup> As

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<sup>2</sup> For a detailed discussion of financial stability aspects of hedge funds, the interested reader is referred to e.g. ECB (2004), SEC (2003) or Brealey and Kaplanis (2001).

<sup>3</sup> See Jorion (2000) for an analysis of LTCM's risk position.

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concerns about a contagious default surged due to the immense size of (levered) LTCM positions, the U.S. Federal Reserve arranged a coordinated bailout by a consortium of the funds' main banks.<sup>4</sup>

This paper deals with one aspect of the hedge fund industry – the classification of funds into homogeneous groups. A consistent classification system is important for numerous reasons – it will help improve investment choices of investors, and funds of funds will refer to it in the construction of their portfolio to avoid undiversified exposures. A natural grouping of funds can furthermore help evaluate the discriminatory power of different styles. In this context, a consistent classification system contributes to an improved performance attribution by peer group analysis (see e.g. the four-factor model of Kandel et al., 2004, in this respect). It can also be useful in establishing risk management models for hedge fund investments.

All of these aspects are in one way or another connected to the safeguarding of financial market stability in that e.g. only diversified (fund) portfolios with an appropriate risk monitoring system in place will enable efficient risk-sharing. Information on hedge fund styles and the probability of funds changing their style over time thereby avoids the exposure of some investors to risks they did not intend to bear and allows other investors to take over the risks they are able to bear with more accuracy. Therefore, information on styles and the likelihood of a style change happening will in the end help increase the shock absorption capacity of financial markets. By the same token, a performance-

based fund selection will ideally help reduce the proportion of untalented managers in the market. With hedge fund manager compensation taking the form of an option (see e.g. Goetzmann et al., 1998), untalented managers depending on luck to “get into the money” are more prone to rely on volatile trading strategies, diminishing the stability of financial markets.

The hedge fund universe itself consists of a great variety of completely different investment and trading strategies. Despite having some common features (unregulated organizational structure, flexible investment strategies, sophisticated investors etc.), hedge funds remain an extremely diverse asset class (see e.g. Ackermann et al., 1999). As a consequence, both practitioners and academics are far from agreeing on a common hedge fund classification system (see Brittain, 2001) – while hedge fund index and database providers rely on their proprietary classification systems, academic research has just begun to adapt mutual fund-based classification methodologies to the idiosyncrasies of the hedge fund business. Several methods of fund classification can be distinguished. The most evident one is fund self-declaration. The problem with this classification method, however, is so-called “style creep,” i.e. the (strategic) misclassification of funds used to polish the fund's own performance with respect to its peers (see e.g. Brown and Goetzmann, 1997). Return-based taxonomies avoid this pitfall by grouping funds along similarities in realized returns. Sharpe (1992) was the first to show that a regression of mutual fund returns on a limited number of indices can be used to spec-

<sup>4</sup> For a detailed discussion of the contagious impact of the LTCM crisis on financial institutions, see e.g. Kho et al. (2000), Furfine (2001) as well as Humayun and Hassan (2004).

ify different fund styles. Both Brown and Goetzmann (2003) and Fung and Hsieh (1997, 1998) expanded these models to the hedge fund universe. Whereas this methodology is very fit for traditional buy-and-hold long-only investments, it is problematic in the case of hedge funds, as is well documented by Fung and Hsieh (1997), due to the unique features of hedge funds, namely dynamic trading strategies including short positions that lead to an averaging error in a standard regression.<sup>5</sup> Alternatively, traditional statistical clustering approaches have been used to classify hedge funds to avoid some of these problems (see e.g. Barès et al., 2001, and Miceli and Susinno, 2003). Both the extensions of Sharpe's style model as well as the clustering applications show that in contrast to findings for mutual funds (see e.g. Brown and Goetzmann, 1997, or diBartolomeo and Witkowski, 1997), self-declared hedge fund strategies are reasonably characteristic of underlying hedge fund styles.<sup>6</sup>

In this paper, we employ a novel methodology to deal with the specifics

of the hedge fund universe. We use Self-Organizing Maps (SOM) to find homogeneous groups of hedge funds based on similar (return) characteristics. The SOM is a neural network-based clustering procedure that maps data points from a higher dimensional space into a lower dimensional space using nonlinear mapping functions. By employing an unsupervised neural network approach which has proven to be reliable in a myriad of disciplines,<sup>7</sup> we are able to avoid a number of problems associated with the regression-based factor approach. As is documented in the literature, the SOM also leads to superior results vis-à-vis traditional statistical clustering approaches such as single linkage, complete linkage, median linkage and K-means.<sup>8</sup> In our paper we demonstrate that the SOM approach is perfectly suited for dynamic trading strategies, which previous models have been unable to deal with efficiently.<sup>9</sup>

As most studies on hedge fund styles are based on samples of return histories up to the year 2000 only and

<sup>5</sup> Recently, contingent claims methodology has been shown to be of value for the classification and/or performance attribution of hedge fund strategies. The work of Fung and Hsieh (2001) and Mitchell and Pulvino (2001) showed, for trend following strategies and merger arbitrage strategies respectively, that option-like features in the strand of Glosten and Jagannathan (1994) capture the underlying risk/return profile of hedge funds much better. See also Agarwal and Naik (2000 and 2002) for a multi-factor approach to evaluate hedge fund performance that is based on option strategies. Note however that, as already pointed out by Glosten and Jagannathan (1994), each strategy requires the use of different (compound) options, making this technique rather hard to handle for classification purposes.

<sup>6</sup> Note, however, that due to the extremely small number of funds analyzed in Miceli and Susinno (2003) – their sample only includes 62 funds – their results may suffer a rather severe sample bias.

<sup>7</sup> In the field of finance, e.g., applications include determining similarities in market timing strategies of investment newsletters (Kumar and Pons, 2002), stock picking (Deboeck and Ulsch, 1998), interest rate structure modeling (De Bondt and Cottrell, 1998) as well as the classification of mutual funds (see Deboeck, 1998, and Moreno et al., 2002).

<sup>8</sup> See e.g. Mangiameli et al. (1996) for the superiority of Self-Organizing Maps as a clustering method for “messy data” sets where the number of clusters is assumed to be known and Ulsch and Vetter (1994) for the case in which the number of clusters (homogeneous groups) in the data are assumed to be unknown a priori.

<sup>9</sup> In a related article, Maillet and Rousset (2003) had a first try at the use of SOM to classify hedge funds. Their results are, however, based on a very narrow sample of funds (294) and are thus likely to display a severe sample bias, as the authors themselves also acknowledge. This may be one reason behind their failure to come up with a well trained map for hedge fund styles.

hedge funds have undergone a spectacular growth since then (see e.g. ECB, 2004, and SEC, 2003), it also seems natural to ask whether results based on the hedge fund market as it was several years ago are representative enough of today’s market environment.

To conclude, our method enables us to derive and visualize a consistent taxonomy for today’s hedge fund market. This will provide us with answers to the following questions:

- Are self-declared hedge fund styles a useful or misleading “label”?
- Do hedge funds change their styles over time, i.e. display so-called “style creep”?
- Are certain groups of funds particularly prone to misclassification?

In our answers to these questions, we can see that hedge funds are not as proficient at assigning themselves to a particular style as previous research suggests. Our results will help improve the choices of investors in terms of the construction of their portfolio as well as contribute to an improved performance evaluation. In view of the opaque nature of the hedge fund business, which is based on proprietary (and secretive) trading strategies, getting the most out of available data seems all the more important for an informed investment decision.

## 2 Methodology

The Self-Organizing Map (SOM)<sup>10</sup> is an ideal tool for clustering and visualizing high-dimensional data; it is a single-layered unsupervised neural

network which does not require any human intervention during the training process.<sup>11</sup> The training process of the SOM can be described as the procedure where the map identifies the key features of the input space via a given set of input vectors. The SOM maps high-dimensional input data into a lower dimensional (usually two-dimensional, hence the term “map”) output space while preserving the inherent structure of the original data input, thus allowing the visualization of complex data sets. Therefore, if two vectors are similar in terms of the distance measure employed, their images will end up in the vicinity of each other on the map. In the present paper, each hedge fund represents an input vector, the dimension of which is given by the number of monthly return observations. After the completion of the training process, hedge funds exhibiting similar return characteristics will be represented as homogeneous clusters on a two-dimensional surface.

In order to represent higher-dimensional data on a two-dimensional map spanned by a single (initially regular) array of nodes, each input vector  $x \in \mathbb{R}^n$  is compared with the parametric reference vector  $m_i \in \mathbb{R}^n$  associated with each node  $i$ . The initial values of the reference vectors are in our case chosen randomly. The location of response is defined to be the node where the distance<sup>12</sup> between the input vector  $x$  and the reference vector  $m_i$  associated with that node achieves a minimum:

$$\|x - m_c\| = \min_i \{\|x - m_i\|\}.$$

<sup>10</sup> The Self-Organizing Map was originally developed by Teuvo Kohonen’s research group and enhanced by many others since the initial publication of the material more than a quarter of a century ago (see Kohonen, 1997, for an exhaustive treatise on the subject).

<sup>11</sup> This characteristic distinguishes the SOM from the “supervised” neural network techniques where both input and output data are fed into the system; a network of that type is useful when a given input-output relationship has to be learned, but it is unfit for our research problem.

<sup>12</sup> The Euclidean distance is used in most practical applications as well as in the present case.

After  $m_c$ , the so-called “winner node”, has been determined, its value as well as that of its neighboring nodes is adjusted toward the value of the input vector  $x$  (this is in fact what constitutes the learning process). Following the completion of all the training passes, each input vector is finally assigned to the trained node most similar in terms of the distance measure employed.

Suppose that we have a finite number of observations indexed by  $t = 1, 2, \dots$  such that the input vector corresponding to observation  $t$  is denoted by  $x(t)$ . The aforementioned adjustments of the winner node  $m_c$  and its neighbor nodes can be expressed in the following fashion:  

$$m_i(t+1) = m_i(t) + \alpha(t)[x(t) - m_i(t)].$$
This learning process is only applied to those nodes  $m_i$  lying within a prespecified distance from the winner  $m_c$ ; the other nodes remain unchanged, i.e.  $m_i(t+1) = m_i(t)$ . The learning rate factor,  $\alpha(t)$  with  $0 < \alpha(t) < 1$ , which establishes the magnitude of the adjustments, as well as the function defining the topological neighborhood of the winner node are both chosen to be monotonically decreasing in time (i.e. the number of completed training passes).<sup>13</sup>

It should be noted that the mapping process is not influenced by dimensions, i.e. return realizations at a given time, which exhibit similar values across all input vectors.<sup>14</sup>

From a more practical side, it should be noted that we use the

original SOM\_PAK library along with an adjusted version of the labeling algorithm of Merkl and Rauber (2001).<sup>15</sup>

### 3 Data

Our paper is based on data from the CISDM (Center for International Securities and Derivatives Markets) hedge fund database. CISDM also provides a summary of the investment strategy and style for each fund. This proprietary classification will be compared to our neural network/return-based classification approach.

The data set includes monthly returns of 5,440 hedge funds until April 2004. In order to avoid what Fung and Hsieh (1997) term “multi-period sampling bias,” which may arise if hedge funds have very short return histories, we only include funds with a minimum of 24 monthly return observations, as recommended by Ackermann et al. (1999). This eliminates 879 funds from our sample. An additional benefit of requiring a minimum length for the return series is increased computational stability. Furthermore, the fund of funds category has been excluded from the analysis a priori in order to allow a focus on the “pure” trading strategies, which reduces our sample by another 853 funds. It should be noted that our results are not subject to survivorship bias, as we include 844 nonsurviving hedge funds in our analysis, i.e. funds which exhibit a minimum number of 24 observations but which have ceased

<sup>13</sup> For specifics regarding the SOM methodology, please refer to Kohonen (1997), Deboeck and Kohonen (1998) or the SOM\_PAK documentation.

<sup>14</sup> If we consider for example the case that all input vectors (i.e. individual hedge funds in our case) feature a return close to 0.1 at dimension 15 (i.e. the 15<sup>th</sup> observation within a fund’s return history), then all trained reference vectors will have a value close to or equal to 0.1 at position 15. Therefore, the absolute distance between each input vector and all properly trained reference vectors with respect to dimension 15 will be very close to zero and hence does not contribute to the determination of the winner node.

<sup>15</sup> The SOM\_PAK was downloaded from [http://ftp.funet.fi/pub/sci/neural/cochlea/som\\_pak/](http://ftp.funet.fi/pub/sci/neural/cochlea/som_pak/).

to exist sometime within the period under observation.

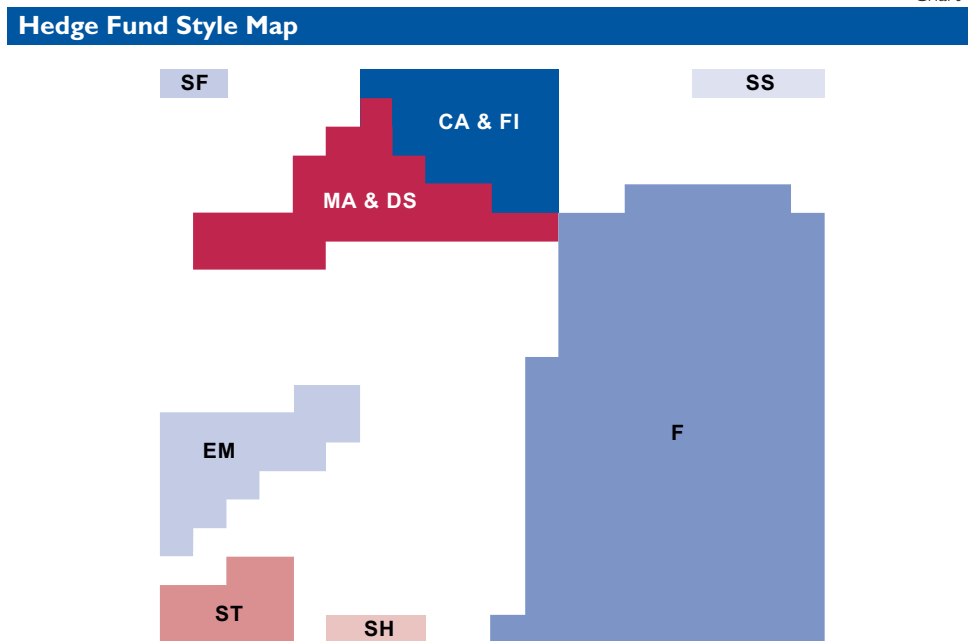
In order to obtain results which reflect the swift development of the hedge fund industry in recent years, we focus our research on the classification of funds in the ten-year period from April 1995 to April 2004. All of the above considered, this leaves us with a total sample of 2,442 funds.<sup>16</sup>

#### 4 Results

The above mapping procedure identifies nine proprietary hedge fund classes (see chart 1 for the resulting

SOM and table 1 for a cross-tabulation of declared versus empirically confirmed hedge fund classes). Following Fung and Hsieh (1997) and Brown and Goetzmann (2003), the labeling is done according to the preponderance of managers of a given self-declared style in each group: convertible arbitrage (CA) and fixed income (FI), emerging markets (EM), futures (F), merger arbitrage (MA) and distressed securities (DS), sector financial (SF), sector health care (SH), sector technology (ST), short-selling (SS) and the class “other,” which encompasses all funds that could not be included elsewhere.

Chart 1



Source: CISDM, own calculations.

Note: A stylized representation of a 20x20 field map trained with our data sample. The hedge fund categories in the table are those adopted from the CISDM database and reflect the self-declared strategies. This particular map has been obtained with the following parameter specifications: rough tuning: Training cycles 13,000,  $\alpha(0)=0.06$ , training radius 11; fine tuning: training cycles 4,000,  $\alpha(0)=0.01$ , training radius 3. However, the results were very stable with regard to changes of parameter settings (within a reasonable margin).

<sup>16</sup> The remaining funds are characterized by the following mixture of (self-declared) strategies: 136 Convertible Arbitrage funds, 74 Distressed Securities funds, 832 Equity Hedge funds, 133 Emerging Markets funds, 821 Futures funds, 80 Fixed Income funds, 76 Global Macro funds, 114 Merger Arbitrage funds, 26 Financial Sector funds, 28 Healthcare Sector funds, 7 Real Estate Sector funds, 46 Technology Sector funds, 25 Short-Selling funds, 27 Multi-Sector funds and 17 Long-Only funds.



These classes occupy sections of different sizes on the map. Whereas managed futures emerge as a large group in this respect, spanning an extensive section of the map, other styles, such as the sector exposed ones (Financial Sector funds, Healthcare Sector funds, Real Estate Sector funds, Technology Sector funds, Short-Selling funds and Multi-Sector funds) occupy relatively little space. The size information can be used to evaluate the degree of dispersion within each of the nine style groups identified, as Euclidean distance is used to depict return similarities on the map.

In contrast to previous research (see Brown and Goetzmann, 2003, or Miceli and Susinno, 2003), our findings suggest that a differentiated picture in the consistency of self-declared

fund styles has to be drawn (see table 1). We can see that some hedge fund styles do a fairly good job of self-classification: Particularly short-sell and sector financial hedge funds, as well as the category comprising managed futures are largely consistent in their self-declared strategies. In all of these cases, more than 65% of the respective funds are clustered in a meaningful way: The fund's self-labeling therefore has economic content in terms of a certain return pattern. Futures and short-sell strategies are especially well grouped by our map, with the percentage of correct self-declaration exceeding 79% in both cases. For managed futures, this underpins the hypothesis that idiosyncratic trading strategies reflected in their returns distinguish them quite substantially from other hedge fund styles.

Table 1

**Declared vs. Empirically Confirmed Hedge Fund Styles**

	CA	DS	EH	EM	F	FI	GM	MA	SF	SH	SR	SS	ST	SMS	LO
CA and FI	54.4	21.6	4.0	8.3	1.8	57.5	10.5	8.8	0	0	0	0	0	0	0
DS and MA	11.0	28.4	5.8	5.3	1.3	3.8	7.9	50.9	0	0	29.0	0	0	0	0
EM	1.5	1.4	4.3	42.1	0.4	0	2.6	0.9	0	0	0	0	6.5	0	5.9
F	1.5	4.1	6.1	1.5	79.5	11.3	35.5	2.6	3.8	0	14.0	0	8.7	0	0
SF	0	0	1.6	0.8	0.2	0	1.3	0	65.4	7.1	14.0	0	0	0	0
SH	0	0	1.2	0	0	0	1.3	0	0	53.6	0	0	0	14.8	0
SS	0	0	1.8	0	0.5	2.5	0	0	0	0	0	88.0	0	0	0
ST	0	1.4	3.1	1.5	0	0	2.6	0.9	0	3.6	0	0	41.3	7.4	23.5
Other	31.6	43.1	72.1	40.5	16.3	24.9	38.3	35.9	30.8	35.7	43.0	12.0	43.5	77.8	70.6
Sum <sup>1</sup>	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Total <sup>2</sup>	136.0	74.0	832.0	133.0	821.0	80.0	76.0	114.0	26.0	28.0	7.0	25.0	46.0	27.0	17.0

Source: CISDM, own calculations.

<sup>1</sup> In percent.

<sup>2</sup> Total number of funds in a given category.

Note: Cross-tabulation of self-declared strategies (rows) with empirically confirmed proprietary strategies (columns). The numbers given are percentage points. The abbreviations denote the following: CA and FI (Convertible Arbitrage and Fixed Income), EH (Equity Hedge and Market Neutral), EM (Emerging Markets), F (Managed Futures), GM (Global Macro), LO (Long Only), MA and DS (Merger Arbitrage and Distressed Securities), SF (Sector Financial), SH (Sector Healthcare and Biotechnology), SS (Short-Sell), SMS (Sector Multi-Sector), ST (Sector Technology).

For several other strategies, we see that a proprietary trading style emerges, but a considerable number of funds misdeclare themselves. In the case of merger arbitrage, convertible arbitrage and fixed income hedge funds, only 50% to 60% of the funds

can be meaningfully grouped with their peers. Furthermore, distressed securities, emerging markets and sector technology funds exhibit a considerable amount of misclassification; The map recognizes these styles, but well over half of the funds pertaining

to one of these self-declared groups are spread over other classes on the map. As a caveat it should, however, be mentioned that all of these styles occupy a rather limited surface on the map and are still able to capture a reasonable percentage of peers within these boundaries. Nonetheless, these results dictate caution in the investment choice and performance evaluation when dealing with the above fund classes.

Furthermore, we detect a number of declared hedge fund styles displaying no or very limited return similarities in our analysis. Especially the so-called “equity hedge” style does not seem to be a useful self-classification. Put differently, this style encompasses too many different substyles that convert the style into a misleading label – “equity hedge” funds are basically spread all over the plane. A similar argument applies for multi-sector and long-only funds, although these funds are more concentrated in several regions of the map without, however, clustering into a homogeneous group. Once again, caution in the construction of fund of funds and in performance attribution has to be exercised with these fund groupings.

In addition to these consistency results, the SOM also detects similarities in a number of declared hedge fund strategies, so that these styles could be interpreted as substitutes in the construction of fund of funds portfolios. Merger arbitrage funds and distressed securities funds, for instance, emerge as a single style. Due to the digital nature of the underlying business (deal closure or not and bankruptcy or not) and the fact that companies that are being taken over are often in a state of financial “distress,” the vicinity of merger arbitrage and distressed securities funds seems

to be perfectly rational from an economic point of view. Convertible arbitrage hedge funds and fixed income hedge funds also appear as a single style on the SOM. Their exposure to bonds can be quoted as a reason for this result. Furthermore, funds with sector exposure (technology, health care, financial, multi-sector) are located in relatively remote sections of the map. The distance of these groups to managed futures, for instance, is in line with the economic rationale that these funds are driven by equity markets to a much greater extent than managed futures are. The map could therefore also be split in terms of equity market exposure, which seems to be important in case of the lower and left section of the plane (see chart 1). This assessment is underpinned by the location of short-sell hedge funds in the opposed (upper right) corner.

In order to analyze the tendency of hedge funds to change their (return-based) style over time, we split our sample into two five-year periods. We exclude funds with less than 110 data points from our analysis to be able to follow the history of hedge funds over our two five-year subperiods and to guarantee enough overlapping returns for computational robustness. This leaves us with 459 funds in the “style creep” sample.

Tables 2 and 3 show the cross-tabulations resulting from the two five-year period maps. In general tables 2 and 3 display higher percentage values for consistent self-declaration, because we restricted our sample quite rigorously to be able to track the history of fund self-declaration. This restriction led to a lower dimensional map (10 × 10 fields versus 20 × 20 fields) and to fewer style groups emerging from the SOM classification



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process (six instead of nine). Furthermore, the fact that our “style creep” sample is now approaching a balanced panel makes the classification task easier for the SOM. Compared to the cross-tabulation in table 1 for the ten-year period map, the identification of fund styles that perform well in their self-classification process and those that do not is largely consistent.

Futures, short-sell and sector financial funds take the lead again, with equity hedge funds spread all over the map. Therefore, the style consistency of different hedge fund groups has by and large remained constant over time. However, the results based on the 1999 to 2004 time period seem to indicate that style inconsistencies of hedge funds were on the rise.

Table 2

**Declared vs. Empirically Confirmed Hedge Fund Styles, 1994–1999**

	CA	DS	EH	EM	F	FI	GM	MA	SF	SH	SS	ST	SMS	LO
CA, DS and MA	95	79	31	0	3	25	0	83	0	0	0	0	20	0
EM	0	0	1	78	0	0	0	0	0	0	0	0	0	0
F	0	7	5	6	91	75	30	0	0	0	0	0	0	0
SF	5	0	9	0	0	0	0	0	100	0	0	0	0	0
SS	0	0	6	6	1	0	0	0	0	0	83	0	0	0
Other	0	14	48	11	6	0	70	17	0	100	17	100	80	100
Sum <sup>1</sup>	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Total <sup>2</sup>	19	14	116	18	232	4	10	23	6	1	6	3	5	2

Source: CISDM, own calculations.

<sup>1</sup> In percent.

<sup>2</sup> Total number of funds in a given category.

Note: Cross-tabulation of self-declared strategies (rows) with empirically confirmed proprietary strategies (columns) for the balanced sample of funds from May 1994 to April 1999. The abbreviations denote the following: CA and FI (Convertible Arbitrage and Fixed Income), EH (Equity Hedge and Market Neutral), EM (Emerging Markets), F (Managed Futures), GM (Global Macro), LO (Long Only), MA and DS (Merger Arbitrage and Distressed Securities), SF (Sector Financial), SH (Sector Healthcare and Biotechnology), SS (Short-Sell), SMS (Sector Multi-Sector), ST (Sector Technology).

Table 3

**Declared vs. Empirically Confirmed Hedge Fund Styles, 1999–2004**

	CA	DS	EH	EM	F	FI	GM	MA	SF	SH	SS	ST	SMS	LO
CA, DS and MA	79	79	17	17	5	25	0	74	0	0	0	0	0	0
EM	0	0	5	50	0	0	0	4	0	0	0	0	0	0
F	16	0	11	6	86	75	30	4	0	0	0	0	0	0
SF	0	0	5	0	0	0	0	0	83	0	0	0	0	0
SS	0	0	3	0	0	0	0	0	0	0	83	0	0	0
Other	5	21	58	28	9	0	70	17	17	100	17	100	100	100
Sum <sup>1</sup>	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Total <sup>2</sup>	19	14	116	18	232	4	10	23	6	1	6	3	5	2

Source: CISDM, own calculations.

<sup>1</sup> In percent.

<sup>2</sup> Total number of funds in a given category.

Note: Cross-tabulation of self-declared strategies (rows) with empirically confirmed proprietary strategies (columns) for the balanced sample of funds from May 1999 to April 2004. The abbreviations denote the following: CA and FI (Convertible Arbitrage and Fixed Income), EH (Equity Hedge and Market Neutral), EM (Emerging Markets), F (Managed Futures), GM (Global Macro), LO (Long Only), MA and DS (Merger Arbitrage and Distressed Securities), SF (Sector Financial), SH (Sector Healthcare and Biotechnology), SS (Short-Sell), SMS (Sector Multi-Sector), ST (Sector Technology).

One should be careful in interpreting the similarity of table 2 and 3 as an indication that funds do not change their style over time. In order to analyze the so-called style creep,

we follow each fund individually to see whether there was a change in the SOM-based style classification from the first period to the second. Table 4 summarizes these results for

the overall sample as well as the individual fund groups. These results indicate that style creep is an issue for the hedge fund industry, with more than 23% of funds changing style over our observation period, although style creep is not as prevalent as in the mutual fund industry (see e.g. Kim et al., 2000, or Gallo and Lockwood, 1999). Overall, it is noteworthy to see that a marked difference in the tendency towards style creep exists between funds that do well in self-declaring (third row in table 4) and funds that do not (second row in table 4). The ex post observed probability of a style change is doubled (11.7% against 23.3%) in the case of hedge funds that misclassify themselves. Our research thereby refines earlier evidence on style shifts by Barès et al. (2001). In a nutshell, one is therefore tempted to conclude “don’t trust a liar.”

Looking at style creep in the different fund categories corroborates this argument. Those fund classes that

have high consistency values in their self-declared styles are less inclined to change a style over time. Futures e.g. seem to be fairly consistent in their intertemporal investment style. Emerging market funds on the contrary seem to be quite inclined to alter their style, whereas for sector financial and short-sell hedge funds the style creep tendency is high for the entire sample but improves markedly for funds that correctly self-classify. As a caveat, it should, however, be considered that not all fund categories occupy the same surface on the map. As Euclidean distance serves as a proxy for similarity, comparatively minor deviations in return characteristics appear as style creep in small fund classes such as short-sell (SS) and sector financial (SF). To sum it up, our analysis documents the presence of style creep in the hedge fund universe, with those funds that misclassify being more inclined to change style.

Table 4

**Style Creep by Hedge Fund Class**

	EM	SF	CA, MA, DS	SS	F
Number Style Creep <sup>1</sup>	7	8	31	6	27
Percentage Style Creep <sup>2</sup>	43.80	47.10	33.70	40	12.10
Number Declared Style Creep <sup>3</sup>	5	1	7	0	20
Percentage Declared Style Creep <sup>4</sup>	35.70	16.70	14.60	0	9.50
Number Correctly Declared <sup>5</sup>	14	6	48	5	210
Total <sup>6</sup>	16	17	92	15	224

Source: CISDM, own calculations.

<sup>1</sup> Based on the mapping results for the 1994–99 subperiod, these numbers indicate the number of funds within a given category which changed their affiliation in the 1999–2004 subperiod.

<sup>2</sup> Percentage of funds (with respect to the category total) within a given category which changed their affiliation in the 1999–2004 subperiod.

<sup>3</sup> Number of funds which correctly classified themselves in the 1994–99 subperiod but changed their affiliation in the 1999–2004 subperiod.

<sup>4</sup> Percentage of funds (with respect to the number of correctly classified funds in a given category) which correctly classified themselves in the 1994–99 subperiod but changed their affiliation in the 1999–2004 subperiod.

<sup>5</sup> Number of funds which correctly classified themselves in the 1994–99 subperiod.

<sup>6</sup> Total number of funds within a given category.

## 5 Conclusion

Despite having some common features, hedge funds remain an extremely diverse asset class. There is no commonly accepted hedge fund taxonomy, as alternating long-short positions are hard to handle with traditional regression-based classification techniques. In this paper we provide a classification of hedge fund styles by detecting hedge fund groupings with similar return characteristics on the basis of Self-Organizing Maps (SOM).

Based on a ten-year sample of 2,442 dead and active hedge funds, we can identify nine hedge fund classes. Earlier findings which document a fairly adequate self-classification of hedge funds (such as Brown and Goetzmann, 2003, and Miceli and Susinno, 2003) can only be partially confirmed. Whereas managed futures and short-sell hedge funds are very consistent in their self-declared strategies, other hedge fund groups (such as fixed income, convertible arbitrage, merger arbitrage, distressed securities, sector technology and sector healthcare funds) exhibit an only moderate aptitude in correctly classifying themselves. Moreover, our results show that several declared hedge fund styles have hardly any similarities and are thus a rather useless label with very diverse return patterns incorporated in these funds (a case in point would be the equity hedge and equity market neutral category). The SOM furthermore detects similarities in a number of declared strategies such as merger arbitrage funds and distressed securities funds.

Looking at a balanced sample of funds for two five-year subperiods, we document that for the second subperiod the overall fraction of correctly self-classified funds diminishes, which implies that since 1999 style inconsistencies have been on the rise. Furthermore, our results suggest that so-called style creep is an issue in the hedge fund universe. It is readily observable in the case of funds belonging to style categories which are particularly prone to erroneous self-classification, e.g. equity hedge funds. It appears that hedge funds belonging to categories which are poor self-classifiers change their (return-based) investment style rather often whereas funds pertaining to more homogeneous categories, such as managed futures or short-sell funds, exhibit more stable and consistent investment behavior.

Our results are important for a number of purposes. The construction of fund portfolios can for instance avoid undiversified exposures to certain styles. Furthermore, a consistent classification can be useful in the construction of benchmarks and thus assist performance attribution. Moreover, fund investors might be interested in their exposure to different fund styles for risk management purposes. In terms of financial stability implications, hedge funds have become an intensely debated issue again recently. In this context, our results help in the construction of diversified (fund) portfolios and thereby enhance the risk-sharing among participants of financial markets. This ultimately increases the capacity of financial markets to absorb shocks.

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