Performance Measurement for Hedge Funds with neural network derived benchmarks*

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Abstract

In this paper, we describe a novel technique for the performance attribution of hedge funds. We use a multi-factor approach in the tradition of Sharpe's (1992) asset class factor model, which we adapt to the special requirements of hedge funds by a new set of benchmark indices. In order to create these indices we use an unsupervised neural network, the so-called Self-Organizing Map. This allows us to group hedge funds into homogenous categories without relying on the funds' error-prone self-classifications. With the constituents of the different strategy categories we construct style consistent benchmark indices that incorporate the dynamic trading strategies distinguishing hedge funds from mutual funds. In the empirical section we assess the usefulness of our performance attribution approach by comparing it with four other models suggested in the literature. For this purpose we evaluate the persistence in the performance of hedge funds and analyze whether fund of hedge funds managers create added value. The results of this empirical analysis show that our performance attribution model is of considerable value in the evaluation of hedge fund performance and the assessment of managers' investment skill and outperforms the tested rivaling models. Moreover our results indicate that investment skill does matter in the hedge fund industry.

Keywords: Performance Measurement, Hedge Funds, Neural Networks

JEL classification: C45, G11, G15, G23

1 Introduction

Measures used to evaluate the performance of mutual funds have evolved from simple CAPM-based models to more elaborate multi-factor models, such as the 8-factor model by Grinblatt and Titman (1988), the asset class factor model developed by Sharpe (1992), the Fama and French (1993) 3-factor model and the 4-factor model by Carhart (1997). These models perform reasonably well with static buy-and-hold long only investments, which are common in the mutual fund universe, but are of limited value for the performance attribution of hedge funds. This is due to the unique features of hedge funds distinguishing them from ordinary mutual funds: Hedge funds employ dynamic trading strategies including alternating long and short positions. Moreover extensive leverage is much more common in the hedge fund industry than in the mutual fund universe. These stylized facts of hedge funds make the models originally designed for mutual funds inappropriate for hedge funds.

More recently, considerable effort went into devising approaches specific to the hedge fund universe (see for example Fung and Hsieh (1997, 2004), Schneeweis and Spurgin (1998), Brown et al. (1999), Ackermann et al. (1999), Agarwal and Naik (2000), Liang (1999), Lhabitant (2001)). The large variety of models most commonly used in performance measurement shows that researchers and practitioners are far from accepting a particular model as the standard.

In this paper, we present a new approach for evaluating the performance of hedge funds which is based on a classical multi-factor model in the tradition of Sharpe's (1992) asset class factor model but uses neural network derived hedge fund indices. With the unsupervised neural network, the so-called Self-Organizing Map (SOM), we group hedge funds into homogenous categories. Kandel et al. (2004) have shown that the use of group-specific benchmark indices, which they call "endogenous" benchmarks, markedly reduces the omitted risk factor problem normally encountered in performance attribution models. The classification of the hedge funds is based on their monthly return histories, which can be assumed to reflect their actual investment style. Thereby we do not need to rely on the funds' self-classifications, which may be biased by fund managers' attempts to polish their historical performance (see e.g. Brown and Goetzmann (1997)). This allows us to create benchmarks indices, which prove in the empirical section to capture the essence of dynamic trading strategies better than traditional models. Moreover our SOM-based benchmark indices can be used to make inferences about the amount of leverage employed by an individual hedge fund.

In the empirical section we use the neural network derived benchmark indices as well as four rivaling models to evaluate a hedge fund's performance and assess a manager's investment skill via the regression's Alpha. Every performance attribution model implicitly claims to distinguish fund mangers with excellent investment skills (significant positive Alpha) from their less talented counterparts. To compare the different performance attribution models, we analyze the evolution of Alphas over time. If a performance attribution model indeed captures the investment ability of a fund's manager this will lead to persistent Alphas. While our SOM-based model exhibits persistent Alpha estimates, all other rivaling models but one fail to have this desired property. The only model that exhibits similar predictive power for future Alphas also uses hedge fund indices as regressors, but is clearly outperformed by our SOM-based benchmark indices in terms of explanatory power. The finding of persistent Alphas does not only underline the usefulness of the hedge fund index-based performance attribution models, but also shows that the manager's investment skill is an important factor in the hedge fund business. Finally, we also analyze whether fund of hedge funds managers create added value. In this analysis we investigate whether managers of fund of funds are able to provide the investor with an excess return through their superior selection of single strategy hedge funds despite the additional layer of fees.

The rest of the paper is organized as follows. In Section 2, we describe the data. Section 3 discusses and compares traditional performance measurement models used in the literature. In Section 4, we show how the neural network benchmark indices are constructed, discuss their out-of-sample performance, and indicate how they can be used to infer the amount of leverage employed by an individual hedge fund. In Section 5, we compare the empirical performance of our model with its closest competitors. For this purpose we use the rivaling models to evaluate the performance and performance persistence of hedge funds and analyze funds of hedge funds. Finally section 6 summarizes and concludes.

2 Data

Our paper is based on monthly return data from the CISDM (Center for International Securities and Derivatives Markets) hedge fund database, formerly known as the Managed Account Reports, Inc. (MAR) database. CISDM also provides a summary of the self-declared investment strategy and style for each fund. This proprietary classification will be used as a basis for the labelling of our SOM-derived clusters and benchmarks. The data set comprises a twelve year time period from May 1992 to April 2004 and contains 5,440 hedge funds. We only include funds with at least 36 monthly return observations in our sample in order to assure a sufficiently high degree of computational stability of the neural network as well as to obtain meaningful estimates in the regression analysis.[1] This eliminates 1,873 funds from our original data set. In a second step we exclude the fund of funds (FOF) category from the benchmark creation in order to ensure that the resulting benchmarks reflect the "pure" trading strategies, which reduces our sample by another 541 funds. Although these 541 funds of hedge funds are excluded from the benchmark creation, we analyze this *FOF Sample* with our suggested performance attribution model (see section 5.2). All of the above considered, this leaves us with a total sample of 3,026 single strategy hedge funds. Table 1 summarizes our data sample.

[Insert Table 1 about here]

We randomly split this sample into two non-overlapping sub-samples. In the first step we use sub-sample one (*SOM Sample*), which consists of 2,026 hedge funds, as a training set for the Self-Organizing Map and subsequently for the construction of our benchmarks. Next we compare the explanatory power of our model with traditional performance attribution models using sub-sample two (*Regression Sample*), which consists of the remaining 1,000 single strategy hedge funds.

[1] The requirement that a fund must have a sufficiently long return history to be included in the sample can give rise to a so-called "multi-period sampling bias." However, according to Fung and Hsieh (2000), the resulting upward performance bias is negligibly small. Ackermann et al. (1999) even find that for their data sample the "multi-period sampling" requirement actually biases their statistics downwards. On the whole, the impact of a required return history of 36 monthly observations appears to be of limited significance.

By construction our data set does not suffer from survivorship bias, as our sample contains 1,607 non-surviving hedge funds, i.e. funds which exhibit a minimum number of 36 observations but which have ceased to exist at some point in time during the period under observation. We also mitigate another problem called either backfilling bias or instant history bias (see Fung and Hsieh (2000)). This bias is caused by the practice of backfilling the historical performance of hedge funds which are newly added to a database. Obviously funds with a good track record are more likely to disclose their historical returns and therefore the backfilling practice causes an upward bias. By requiring at least 36 monthly return observations the effects of the backfilling bias should be markedly reduced, as the historical returns backfilled typically contain the last 12-15 months (cf. Fung and Hsieh (2000), p. 298).

3 Traditional Models for Measuring the Performance of Hedge Funds

In this section we present and evaluate six traditional performance attribution models. All models discussed can be interpreted as special cases of the general Sharpe (1992) model, which is an asset class factor model of the following form:

$$R_{i,t} = \alpha_i + \sum_k \beta_{i,k} F_{k,t} + \epsilon_{i,t} \tag{1}$$

where F_1 to F_K are the returns of k different asset classes and $\beta_{i,1}$ to $\beta_{i,K}$ represent the sensitivities of R_i, the fund i's return, to these k asset classes. The sensitivities $\beta_{i,k}$ can be interpreted as the exposure of the analyzed fund (or portfolio) to these asset classes. Models of this type attempt to separate a managed portfolio's returns into a component which can be easily replicated via the returns on standard asset classes and a remaining component, the so-called "Jensen's Alpha" (α_i), which captures the manager's investment skill (cf. Jensen (1968)).

We analyze the applicability of the following six models for performance attribution in the hedge fund universe with the *Regression Sample* comprising 1,000 single strategy hedge funds:

- Models designed for mutual funds
  - The Capital Asset Pricing Model (CAPM) independently suggested by Sharpe (1964), Lintner (1965) and Mossin (1966)
  - The three-factor model of Fama and French (1993)
  - The four-factor model of Carhart (1997)
- Models designed for hedge funds
  - The asset class factor model of Fung and Hsieh (1997)
  - The asset-based style factor model of Fung and Hsieh (2004)
  - The hedge fund index multi-factor model suggested by Lhabitant (2001)

The first three models are based on the CAPM and therefore the regression equations are formulated in excess of the risk free rate.[2] All of them have been developed for performance attribution in the mutual fund universe and for that reason do only include equity market specific risk factors.[3] The Fung and Hsieh (1997) model, which covers the equity, fixed income, currency and commodity markets, includes all major asset classes used by hedge fund managers.[4] Fung and Hsieh (2004) go one step further by including regressors having a nonlinear exposure to the standard asset classes. Their Asset-Based Style (ABS) factors "link returns of hedge fund strategies to observed market prices".[5] The multi factor model of Lhabitant (2001) finally uses the strategy sub-indices of the CSFB/Tremont hedge fund index family as risk factors.[6]

[2] We use the return on the one-month Treasury Bill rate as a proxy for the risk-free interest rate.

[3] The risk factors are available for download on Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french . As a proxy for the Carhart (1997) momentum factor we have used the UMD momentum factor supplied by Kenneth French.

[4] Information on the used risk factors (datastream codes) is available on David Hsieh's website: http://faculty.fuqua.duke.edu/ dah7/8FAC.htm .

[5] cf. Fung and Hsieh (2002), p.16. The ABS factors are also available on David Hsieh's website: http://faculty.fuqua.duke.edu/ dah7/HFRFData.htm .

[6] The times series of the employed hedge fund indices can be downloaded from the following website: www.hedgeindex.com .

[Insert Table 2 about here]

Table 2 presents an overview of the explanatory power achieved by the different performance attribution models for the *Regression Sample*. As the analyzed models don not have the same number of explanatory variables we use the adjusted R^2 statistic to compare them. This goodness-of-fit measure has the desirable property that its value does not automatically increase when additional explanatory variables are included (see e.g. Verbeek (2004)). The median adjusted R^2 of all funds analyzed tells us that there are considerable differences between the studied models. In the case of the four-factor Carhart (1997) model, which is still the best of the three CAPM-based models, more than 50% of all funds display an adjusted R^2 below 0.09. As expected the three models especially designed for hedge funds do a better job with a median R^2 of 0.15 for the Fung and Hsieh (1997) asset class factor model, of 0.20 for the Fung and Hsieh (2004) asset-based style factor model and of 0.29 for the hedge fund index model of Lhabitant (2001). The lowest adjusted R^2 of the 25% best explained funds is about 0.30 for all models except the CAPM which performs considerably worse (0.19) and the hedge fund index model of Lhabitant (2001) which performs considerably better (0.47). Overall it can be said that the CAPM-based models originally designed for mutual funds are inadequate for performance attribution in the hedge fund universe. But also the asset class factor model of Fung and Hsieh (1997) and the asset-based style factor model of Fung and Hsieh (2004) do not perform exceptionally well. Only the hedge fund index multi-factor model suggested by Lhabitant (2001) displays a satisfactory explanatory power.

This comparison of R^2s clearly shows that all asset class factor models using the Sharpe (1992) setup together with risk factors having a linear exposure to the standard asset classes (CAPM, Fama and French (1993), Carhart (1997) and Fung and Hsieh (1997)) display a low explanatory power for single strategy hedge funds. This inadequacy is due to the unique features of hedge funds. Dynamic trading strategies and the extensive use leverage distinguish hedge funds from most mutual funds. The consequences of dynamic trading strategies are alternating long and short positions within a certain asset class resulting in a regression coefficient for that asset class close to zero. In Sharpe's framework, this would imply that a particular hedge fund that invests its entire capital in the bond market and uses a dynamic trading strategy could be characterized as having no exposure to the bond market at all, if he alternates long and short positions within that asset class (cf. Fung and Hsieh (1998), p. 10). This potentially problematic feature of the model was already recognized by Sharpe who stated that “the style identified [...] is, in a sense, an average of potentially changing styles over the period covered.”(cf. Sharpe (1992), p.11.) While the averaging error is of minor importance for most mutual funds, it makes the asset class factor model useless for hedge funds, which are frequently switching from long to short positions and vice versa.

In principle, there are two distinct ways of dealing with the dynamic nature of hedge fund investment strategies for performance measurement purposes. The first way is to use standard asset classes as regressors and to allow for time-varying factor loadings. This can be implemented using a linear regression model with rolling windows[7] (see e.g. McGuire et al. (2005)) or various types of generalized autoregressive conditional heteroscedasticity (GARCH) models, stochastic volatility (SV) models or Kalman filter based approaches (for a recent comparison of alternative modelling techniques as applied to time-varying CAPM betas see Mergner (2005)).

The second way of capturing the dynamic components of hedge fund investment strategies is by including regressors with non-linear exposures to standard asset classes, which then serve as proxies for the dynamic trading strategies. Using regressors that already incorporate the dynamics of hedge fund investment styles opens up the possibility of using a simple linear regression framework for performance measurement in the hedge fund universe while still allowing for non-linearities in the analysis via the “dynamics” embedded in the regressors.

A first approach for identifying regressors, which feature a non-linear exposure to the underlying asset classes, is to use specifically constructed indices for each hedge fund style category. Fung and Hsieh (2002) have suggested this type of indices termed “asset-based style (ABS) factors”, which account for dynamic trading strategies by using mostly contingent claims. The

[7] Rolling window regressions have two drawbacks. First the choice of window is somewhat arbitrary and will nonetheless severely affect the resulting coefficient estimates. It is hard to say ex ante whether e.g. a 12 month or 24 month window is appropriate. Second it is clear that the parameter estimates will be rather imprecise since the procedure does not make use of the full data sample but only of the number of observations in a given window frame.

Fung and Hsieh (2004) model analyzed above uses the ABS factor approach. Unfortunately only a limited number of such ABS factors have been identified in the literature so far.[8] Furthermore we assume that many of the discretionary investment strategies with the formidable set of investment possibilities open to hedge funds will be hard if not impossible to explain in the way described by Fung and Hsieh (2002, 2004). The performance measurement models based on hedge fund indices, which are discussed below, clearly capture a higher fraction of the hedge fund return variance than the Fung and Hsieh (2004) model. The low average adjusted R^2 of their Asset Based Style factor model indicates that the seven risk factors identified by Fung and Hsieh (2004) might not be sufficient to explain the risk in the returns of individual hedge funds and it is likely that some risk factors important for hedge funds are omitted. Fung and Hsieh (2004) point out themselves that "as one moves away from a well-diversified portfolio of hedge funds to more specific hedge fund styles - and eventually to individual funds - one cannot escape the burden of constructing additional risk factors that are specific to the styles."[9]

Another approach that stays in the linear regression framework while at the same time keeps track of the dynamic nature of hedge fund trading strategies is to use hedge fund indices. This approach can also mitigate the omitted risk factor problem, because hedge fund indices contain all the risk factors that the constituting funds are exposed to. While hedge fund indices cannot explicitly link hedge fund returns to specific risk factors, the indices can nonetheless act as useful proxies for those risk factors for all practical purposes such as performance attribution. Lhabitant (2001) for example suggests to use the freely available CSFB/Tremont hedge fund index family. Unfortunately, this particular approach suffers from several major drawbacks. First of all, the number of strategy categories employed (i.e. the number of indices used as regressors) is somewhat arbitrary and hence not optimal. Secondly, data vendors constructing hedge fund indices typically rely on the self-proclaimed style labels given to the funds by

[8] Fung and Hsieh (2001) suggest a portfolio of lookback straddles on currencies, commodities, three-month interest rates, bonds and equities to explain the returns of trend-followers in futures markets. Another example is the Risk Arbitrage Index constructed by Mitchell and Pulvino (2001) by analyzing 4750 mergers between 1963 and 1998. The authors show that this index is able to successfully explain the returns of merger arbitrage hedge funds.

[9] cf. Fung and Hsieh (2004), p.78.

their managers.[10] Inevitably, the prevailing misclassification and style drifts in the hedge fund business markedly reduce the usefulness of hedge fund indices as proxies for the dynamic trading strategies of particular hedge fund investment styles.[11] It is also well documented that there is considerable heterogeneity within self-declared hedge fund styles, which can be readily seen by the low correlations between the monthly returns of hedge funds within a given style category.[12] Thirdly, when analyzing persistence in performance of hedge funds over time, the use of common hedge fund indices has the disadvantage that these indices are re-balanced regularly and that they do not represent the same composition during a given period of interest. Therefore, persistence estimates would likely be erroneous, as pointed out by Gregoriou et al. (2005). In the following section, we present an approach for constructing hedge fund benchmark indices which is able to take account of these concerns.

4 Neural Network-based Hedge Fund Indices

4.1 SOM Methodology

The Self-Organizing Map (SOM)[13] is a well-proven tool for grouping and visualizing high-dimensional data; it is a single-layered unsupervised neural network which does not require any human intervention during the training process.[14] The SOM maps high-dimensional input data into a lower dimensional output space (usually two-dimensional, hence the term "map")

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[10] A notable exception are the hedge fund indices by Zurich Capital Markets which use both qualitative criteria as well as statistical clustering procedures for the construction of the indices. However, these indices only go back to 1998 and due to the way they are constructed they exhibit a severe selection bias (the indices are based on only 60 funds and the constituting funds are hand picked according to a number of constraints, such as reporting requirements, minimum years in existence and assets under management). For details see Amenc et al. (2003).

[11] For an analysis of misclassification and style drifts in the hedge fund universe, see Bares et al. (2001), Amenc and Martellini (2003), and Baghai-Wadji et al. (2005)

[12] For example, Edwards and Caglayan (2001) document that the medians of the pairwise correlation coefficients range from 0.09 for the market-neutral to 0.53 for the short-selling category.

[13] 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 (2000) for an exhaustive treatise on the subject).

[14] 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 unsuitable for our research problem.

while preserving the inherent structure of the original data input. In the present paper, the return time series of 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 are assigned to the same region of the map.

The classification of hedge funds with the SOM proceeds in the following steps:[15]

- **Step 1:** First the number of nodes, which are located on a lattice, has to be specified. We work with a quadratic lattice of 20x20 nodes, which is adequate for the clustering via visualization[16] that our work is based on. Each node is represented by its reference vector $m_i(t)$. The dimension of the reference vector depends on the number of features characterizing the input. In our case the input is the set of individual hedge funds used for training the map and their features are the 144 monthly returns covering the period May 1992 to April 2004. The initial values of the reference vector are randomized.

- **Step 2:** Next, the actual training process takes place. The first input vector $x(t)$, which is chosen randomly (sampling without replacement), is presented to the map. This means that the similarity between the input vector and each reference vector is computed. We use the Euclidian distance as the measure of similarity. The winning node is defined as the node with the smallest Euclidian distance.

- **Step 3:** Once the winning node is determined the actual learning starts. The winning node as well as his neighboring nodes are updated. The actual radius around the winning node within which the nodes are updated starts with the user defined initial value and constantly decreases in the course of the training. In the updating process the reference vectors $m_i(t)$ of the nodes in the vicinity of the winning node (for example all nodes within a radius of 3 nodes) are adjusted towards the input vector $x(t)$. The adjustment is determined by the following formula:

[15] cf. Kohonen et al. (1995).

[16] For a discussion of the distinction between SOM for clustering, SOM for simultaneous clustering and visualization, SOM for visualization and SOM for clustering via visualization see Flexer (2001).

$$m_i(t+1) = m_i(t) + \alpha(t) \cdot [x(t) - m_i(t)] \quad (2)$$

where $\alpha(t)$ is the learning rate factor, with $0 < \alpha(t) < 1$. If α were one, the adjusted nodes would be immediately set equal to the presented input vector.

- **Step 4:** The next input vector is chosen randomly and the process is repeated starting from Step 2 until the user defined number of training cycles is completed. In the case of 10,000 training cycles each of the approximately 2,000 hedge funds is presented about 5 times to the map. During the training process, the updating radius as well as the learning rate factor $\alpha(t)$ are linearly decreased after each training cycle (consisting of step 2 and 3). The decrease ensures that the two variables run from their initial value to zero during the course of the training.

- **Step 5:** Finally each fund is assigned to the node that has the reference vector with the smallest Euclidian distance.[17] If two input vectors are similar in terms of the distance measure employed, they will finally be assigned either to the same node or at least to neighboring nodes on the map.

The training process of the self organizing map is divided into a rough tuning and a fine tuning phase.[18] In the rough tuning or ordering phase the training starts with a higher radius of e.g. 10 (half the diameter of our map) for updating the map and a learning rate factor α of 0.05, for example. When a hedge fund is used to update the previously determined winning node and its neighboring nodes it becomes more likely that the winning node for another fund having similar return characteristics will be among those updated nodes. At the same time it becomes increasingly unlikely that a node of the updated section will be the winning node for a hedge fund with very different return characteristics. The rough tuning phase ensures that nodes with reference vectors representing very different return characteristics will not end up in vicinity of each other and a rough classification is established.

[17] At this stage it is possible to present new hedge funds to the map that were not used for the training, which allows for the subsequent classification of these funds.

[18] cf. Kohonen et al. (1995), p. 17.

During the second phase, the fine tuning starts with lower parameter values, e.g. 3 for the radius and 0.01 for the initial α. Hence in the course of the fine tuning only close-by nodes are updated and a precise discrimination within clusters, which were already determined during the rough tuning, is established.

The SOM algorithm requires the following user defined parameters and inputs for the training:

- The input vectors used for the training
- The dimension of the lattice, i.e. the number of nodes
- The rough and the fine tuning phase require each:
  - The number of training cycles
  - A starting value for the learning rate factor
  - A starting value for the radius defining the neighborhood

As has been shown by Cottrell et al. (2001) the SOM algorithm is highly insensitive with respect to the chosen initial parameter values.

[Insert Table 3 about here]

In the following paragraph we discuss the implications of using the Euclidean Distance as similarity measure in connection with return time series, which is a particularity of our SOM application. Table 3 shows a stylized example of four different funds with a monthly return time series covering half a year. Fund A acts as the reference and could for example be a convertible arbitrage fund (for summary statistics of different self declared fund styles see table 1). The managers of fund B and C use the same investment style but employ more leverage, resulting in an increased standard deviation (50% higher for fund B and 100% higher for fund C). Fund D acts as our example of dissimilarity, because it is perfectly negatively correlated with the other three funds. The highly levered Fund C displays a considerable Euclidean distance (0.036) to Fund A, although both follow exactly the same convertible arbitrage strategy. These two funds will therefore be assigned to nodes which are most likely not adjacent. But we can see that Fund A as well as Fund C have both a low Euclidean distance to Fund B (0.018) and will therefore be assigned to nodes in the neighborhood of Fund B. This mechanism ensures that a convertible arbitrage cluster emerges on the map. Fund D on the other hand, which follows the opposite strategy of a convertible arbitrage fund, has high Euclidean distances to all three "CA" funds (>0.070) and will therefore end up in a section of the map far away from the convertible arbitrage cluster. This example illustrates how different standard deviations are handled by the SOM algorithm. The return time series we use as input vectors obviously have all (central) return moments embedded. Two funds will only have a Euclidean distance of zero if they are perfectly correlated and all return moments match. Every deviation in the return moments will produce an increased Euclidean distance and consequently is detected by the SOM algorithm.[19] We therefore refrain from explicitly including higher return moments into the input vectors used for training the SOM and do not use any other fund characteristics either. diBartolomeo and Witkowski (1997) have pointed out that return-based classification methods have several advantages over methods which are based on other characteristics to classify funds. To be specific, returns are, in the end, what investors are interested in and they fully characterize the employed trading strategy of a particular hedge fund manager. As we use net returns for training the map the fee structure of a particular fund is implicitly contained in the input vector. A special feature of the SOM algorithm is its ability to cope with missing values in the input vectors.[20] This is essential for our application as few of our funds have a return time series covering the entire 12 year period from 1992 to 2004.

Finally the following considerations determined our choice of a 20x20 map dimension. As the correct number of hedge fund strategy cluster is not known a priori, we can not set the number of nodes equal to the number of clusters in the data, which is a prerequisite for using the SOM to directly divide the set of hedge funds into a prespecified number of clusters. This information would also allow us to use one of the traditional clustering algorithms. Therefore we have to rely on clustering via visualization, which is the typical application of Self Organizing Maps in

[19] The impact of the different return moments on the Euclidean distance is however not necessarily of the same order of magnitude.

[20] cf. Kohonen et al. (1995), p. 3.

the field of finance (cf. Deboeck and Kohonen (1998)). Clustering via visualization requires a considerably higher number of nodes than the assumed number of clusters to avoid negative effects from the discretization of the SOM's output space (cf. Flexer (2001), p. 381). We therefore use a quadratic 20x20 lattice resulting in 400 nodes. This specification alleviates the discretization problem, but still avoids large empty sections on the map with several nodes not even included in the training process and Euclidean distances loosing their discriminatory power, which happens in the case of a too high map dimension.

4.2 Construction of the SOM-based strategy indices

Our benchmark construction consists of two steps. In the first stage we use the SOM algorithm in order to group hedge funds according to their innate return characteristics rather than rely on their self-proclaimed investment styles. In the second stage we use all funds establishing a strategy cluster detected by the SOM to construct our benchmark indices.

The clustering procedure starts by training the Self-Organizing Map with our *SOM Sample* comprising 2,026 funds. On the resulting map the strategy clusters are determined with the following procedure. In accordance with Fung and Hsieh (1997) and Brown and Goetzmann (2003), the labelling of the distinct style categories is done according to the preponderance of managers of a given self-declared style in each cluster. We label a node with a specific style, if funds having this self declared trading style constitute the largest individual group and account for at least 40% of all funds assigned to that node. When the entire map is labelled according to this rule adjacent nodes having the same style label automatically evolve as clusters. This mechanical labelling / clustering procedure eliminates the subjectivity typically connected with clustering via visualization. Applied to our map this procedure detects eleven clearly discernable strategy clusters: Convertible arbitrage (CA), distressed securities (DS), emerging markets (EM), fixed income (FI), currency futures (FUC), diversified futures (FUD), merger arbitrage (MA), sector financial (SF), sector healthcare (SH), short selling (SS) and sector technology (ST).[21] An advantage of this clustering procedure is that we do not need to

[21] Note that for equity hedge funds this procedure always resulted in the identification of multiple smaller scattered clusters, which were not connected to each other. For this reason it was not possible to locate a

specify the number of clusters in advance.

The strategy clusters identified in the first step are then used to construct corresponding benchmark indices which serve as a proxy for the dynamic trading strategy. This is achieved by forming an equally weighted portfolio of all funds constituting a given trading strategy cluster. Suppose we have identified a cluster representing the trading strategy "Convertible Arbitrage". To calculate the benchmark index "CA" representing this (dynamic) investment strategy, we compute the mean return of the funds in the given cluster for each month t:

$$CA_t = \frac{1}{N_t} \sum_{i=1}^{N_t} R_{i,t} \tag{3}$$

where CA_t is the time t return representing the trading strategy "Convertible Arbitrage," $R_{i,t}$ is the time t return of fund i in the Convertible Arbitrage cluster and N_t is the number of funds in the "CA" cluster that have a return observation in month t. Some of the funds used for the construction of the "CA" benchmark have other self-declared style labels than Convertible Arbitrage but according to our SOM classification produce returns corresponding to a "CA" strategy. This might be due to the fact that two different trading style labels actually describe the same investment strategy or can be caused by intentional or unintentional misdeclaration. Repeating this calculation for each month in the sample period delivers the return history of the "Convertible Arbitrage" benchmark. Proceeding analogously for all the style clusters on the SOM's surface gives us the desired set of benchmark indices representing all hedge fund trading strategies producing unique return patterns.

These points are in fact important for distinguishing our model from other "peer-group" approaches and eliminate most drawbacks typically connected with this type of approach (see Fung and Hsieh (2002) and the discussion of Lhabitant's (2001) model in section 3). Instead of relying on an ad hoc classification of hedge funds based on self-declared strategies, we identify and incorporate into our model specification only those style groups which also produce a sufficiently discernable and characteristic return pattern. In addition, our indices are also, to

single homogenous equity hedge cluster on the map. Given the generally low correlations between funds in this self-declared category (see Edwards and Caglayan (2001) and Schneeweis et al. (2004)), this result is hardly surprising.

the largest possible extent, "purified" from data biases that standard hedge fund indices inherit from the databases underlying their construction. This is due to the fact that we specifically adjust for survivorship bias by including non-operating hedge funds in our training sample; furthermore, we mitigate the concern regarding instant-history (backfilling) bias by requiring a minimum return history of three years.

As expected the cross-correlations between our benchmark indices are rather low (for details see table 10). This supports our claim that all SOM derived strategy benchmarks represent unique return patterns and furthermore avoids multi-collinearity problems in the regression analysis performed in the following section. The correlation coefficient between the merger arbitrage (MA) and distressed securities (DS) benchmark indices is with 0.62 one of the highest. This can be explained by the digital nature of the underlying business (deal closure or not and bankruptcy or not) and by the fact that companies that are being taken over are often in a state of financial "distress."

[Insert Table 10 about here]

4.3 Regression results for the SOM-based strategy indices

Using the benchmark indices, we specify the following multi-factor model:

$$\begin{aligned} R_{i,t} = \alpha_i &+ \beta_{i,1} CA_t + \beta_{i,2} DS_t + \beta_{i,3} EM_t + \beta_{i,4} FI_t \\ &+ \beta_{i,5} FUC_t + \beta_{i,6} FUD_t DS_t + \beta_{i,7} MA_t + \beta_{i,8} SF_t \\ &+ \beta_{i,9} SH_t + \beta_{i,10} SS_t + \beta_{i,11} ST_t + \varepsilon_t \end{aligned} \tag{4}$$

where $R_{i,t}$ is hedge fund i's return and the right-hand side explanatory variables are the returns on the SOM-based benchmarks (Convertible arbitrage (CA), distressed securities (DS), emerging markets (EM), fixed income (FI), currency futures (FUC), diversified futures (FUD), merger arbitrage (MA), sector financial (SF), sector healthcare (SH), short selling (SS) and sector technology (ST)).

The last column of table 2 gives the adjusted R^2 statistic that our SOM-based benchmarks achieve for the *Regression Sample* of 1,000 funds. As can be seen from the table, our benchmarks produce very satisfactory regression results, in particular when compared with the models discussed in section 3, which are commonly used in the literature and real-world applications (i.e. CAPM, Fama and French (1993), Carhart (1997), Fung and Hsieh (1997), Fung and Hsieh (2004) and Lhabitant (2001); see table 2). The adjusted R^2 is above 0.35 in more than half of the regressions (compared to 0.29 for the CSFB/Tremont indices and 0.20 for the Fung and Hsieh (2004) model) and above 0.55 in more than 25% of the regressions (compared to 0.47 for the CSFB/Tremont indices and 0.33 for the Fung and Hsieh (2004) model). The empirical distribution of the R^2 statistic depicting the explanatory power of our benchmarks for the *Regression Sample* in figure 1 shows that our SOM based benchmarks perform better than all evaluated alternatives.

Since our benchmarks are exclusively constructed with funds which are not in the *Regression Sample*, whereas the CSFB/Tremont indices used by Lhabitant (2001) are very likely to contain some of the funds analyzed, it is remarkable that our benchmarks achieve higher R^2s than the CSFB/Tremont hedge fund indices. One particular difference between the CSFB/Tremont hedge fund indices and our benchmarks is the fact that in the creation of our benchmarks all funds receive the same weight whereas the CSFB/Tremont indices are value-weighted. However, the most likely reason for the superior performance of the SOM-based indices is that they have been designed to be style consistent and that the number of regressors included in our model specification is not arbitrary but based on the return characteristics of the hedge fund universe.

[Insert Figures 1, 2, 3 and 4 about here]

A style regression using the SOM-based benchmarks as regressors sheds light on some of the more opaque hedge fund trading styles. Figure 2 shows the number of regressions in which a particular SOM-based strategy benchmark evolved as the most significant regressor for the sub-sample of all self-declared equity hedge funds in our *Regression Sample*. It can be seen that equity hedge funds seem to pursue various trading strategies, although one can detect a tendency towards the equity oriented trading styles, which are represented by the Sector Financial, the Sector Healthcare, the Short Selling and the Sector Technology benchmark indices. Overall, this style regression seems to confirm the finding of Baghai-Wadji et al. (2005) that the equity hedge style encompasses a number of sub-styles with very different return patterns.

Figure 3 shows that managed futures funds produce a very distinctive return pattern, which clearly distinguishes them from other hedge fund strategies. Moreover figure 3 supports the finding of Baghai-Wadji et al. (2005) that most managed futures funds are very consistent in their self declaration.

Figure 4 depicts the number of regressions in which a particular SOM-based strategy benchmark evolved as the most significant regressor for the sub-sample of all self-declared global macro hedge funds. One interesting finding, obvious from eyeballing figures 3 and 4, is the broad similarity in the return patterns of global macro funds and managed futures funds. Apparently, the macroeconomic bets of global macro funds take place in the same asset classes that managed futures funds are active in. If one thinks of George Soros' Quantum fund and the devaluation of the British pound, one would be inclined to point at currency futures as the driving factor in explaining the returns of global macro funds. However, according to our style regression, diversified futures funds are better at explaining the variability of global macro fund returns than currency futures funds. This indicates that global macro funds are very active in at least one of the asset classes traded by diversified futures, such as commodities or interest rate futures.

4.4 Inferring the level of leverage

Typically, it is unclear with how much leverage a particular hedge fund operates, as most funds are rather secretive with respect to this point and leverage might also stem from the instruments used. Regressing the returns of individual hedge funds on the set of our SOM-based strategy benchmarks provides an answer to this question.

The SOM-based strategy benchmarks reflect the level of gearing used by the average fund manager adhering to the represented trading style. Therefore, we can interpret the regression coefficients of the style regression as leverage indicators. For an individual fund a regression coefficient greater than one indicates an above average use of leverage and vice versa. Hence, the regression coefficients of the multivariate regression provide information on the relative amount of leverage employed by an individual fund. With the help of our database we are able to estimate the absolute level of leverage represented by each SOM-based strategy benchmark. For this purpose we calculate the average leverage level of all funds constituting a particular SOM-based strategy benchmark. This information allows us to infer the absolute amount of leverage of an analyzed fund by multiplying all significant regression coefficients with the leverage levels of the respective SOM-based strategy benchmarks. In the case of publicly available hedge fund indices like the CSFB/Tremont hedge fund index family, leverage information is typically not available. As a consequence, the advantage of our SOM-based benchmarks is that they can help to shed light on the absolute level of leverage, while standard hedge fund indices, which lack leverage information, do only allow for relative leverage estimates.

In order to analyze the accuracy of the absolute leverage estimates, we test the proposed procedure with all *Regression Sample* funds that feature leverage information. For the calculation, we regress the returns of the individual funds against the SOM-based strategy benchmarks with the highest explanatory power and then multiply the absolute value of the resulting regression coefficient with the mean leverage level of the respective SOM-based strategy benchmark given in the first column of table 4. From the comparison of the resulting estimates with the self declared leverage figures it can be said that the estimator seems to be unbiased, but in many cases very unreliable. It is obvious that the accuracy of the leverage estimator should rise together with the R^2 of the regression used to calculate it. Considering all funds with an R^2 higher than 40% the correlation coefficient between the declared leverage figures and the calculated estimates is 0.28. Restricting the sample to all funds with an R^2 above 80 % the correlation coefficient rises to 0.62. Therefore we can conclude that the leverage estimator is only reliable for hedge funds, whose returns are well explained by the SOM-based strategy benchmarks.

[Insert Table 4 about here]

Table 4 reports the means and median amounts of leverage incorporated in our SOM-based strategy benchmarks. Fixed Income (FI) hedge funds and Convertible Arbitrage (CA) hedge funds are particularly highly levered. There exists not only a high degree of heterogeneity with respect to the amount of leverage employed across different style categories, but also within a given style category, which can be seen from the last column of table 4. Comparing table 1 and table 4 leads to the initially rather counterintuitive finding that the strategies employing the highest amount of leverage tend to report the returns with the lowest volatility. A case in point would be the Fixed Income (FI) category, which has a rather low average return volatility but employs a considerable amount of leverage. This phenomenon can be explained by the fact that strategies with moderate core risk tend to operate with more leverage than those strategies with a high inherent risk level. Furthermore an increasing level of leverage might not directly translate into riskier returns when managers adjust their trading style in line with the amount of leverage they operate with. This behavior might be imposed upon the managers by their creditors (see Schneeweis et al. (2005)).

5 Performance analysis with neural network derived benchmarks

The main question of interest in performance measurement is whether or not an individual hedge fund manager can create additional value when the performance of his fund is compared with suitably chosen benchmarks. For this purpose we specify the multi-factor model presented in the previous section in excess return form:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i &+ \beta_{i,1}(FUC_t - R_{f,t}) + \beta_{i,2}(FUD_t - R_{f,t}) + \beta_{i,3}(ST_t - R_{f,t}) \\ &+ \beta_{i,4}(SH_t - R_{f,t}) + \beta_{i,5}(SS_t - R_{f,t}) + \beta_{i,6}(DS_t - R_{f,t}) + \beta_{i,7}(MA_t - R_{f,t}) \\ &+ \beta_{i,8}(FI_t - R_{f,t}) + \beta_{i,9}(CA_t - R_{f,t}) + \beta_{i,10}(EM_t - R_{f,t}) + \beta_{i,11}(SF_t - R_{f,t}) + \varepsilon_{i,t} \end{aligned} \tag{5}$$

The Alpha in the regression above is not directly comparable to "Jensen's Alpha", but can be interpreted as the excess investment ability of an individual manager relative to his peer group of hedge fund managers (see also Kandel et al. (2004)). This is due to the fact that we as well as Lhabitant (2001) use hedge fund indices as regressors. In this case the regressors already contain the Alpha that an average hedge fund creates, which may be positive, negative or zero. Hence, the average Alpha from regressing a random sample of hedge funds should be zero and deviations from this value must be due to special features of the sample. The same holds for the average Alphas of specific strategies. Nevertheless, looking at the Alphas of individual funds is perfectly sensible, because it can elucidate whether one particular fund manager produces abnormal returns relative to other hedge funds.

5.1 Persistence of Alphas

The idea behind all performance attribution models is that the calculated Alpha reflects the investment skill of the manager. If that is the case and skill matters, we should find persistence in the calculated Alphas over time. Therefore the persistence of Alphas is a good criterion to asses the quality of different performance attribution models. Using this procedure we compare our SOM-based model with the three hedge fund performance attribution models introduced in section 3 and the Carhart (1997) model. In this section we only test the Carhart (1997) model out of the three models for mutual funds, because it nests the CAPM and the Fama and French (1993) model and in addition produces higher adjusted R^2s.

In order to compare the performance of the five analyzed models we split our twelve year sample period into four non-overlapping three year subperiods and calculate the Alphas for all funds in the *Regression Sample*. Next, we sort the 1000 funds into quartiles with respect to their Alpha in each individual subperiod. This information is used to calculate transition probabilities for the subsequent subperiod revealing e.g. the likelihood of a first quartile hedge fund staying in the top quartile for the next three year period. This is one of five possible events: In general, a fund can end up in one of the four quartiles or it can stop reporting its performance to the database.

A fund manager might cease reporting for various reasons, of which probably the most obvious is poor performance followed by a closure of the hedge fund. Alternatively, it could be argued that since hedge funds by their very nature try to exploit market inefficiencies, the capacity and possible fund size is limited (see for example Agarwal et al. (2003), who document decreasing returns to scale in the hedge fund industry). Therefore, a fund, which has reached its capacity limit in terms of investment volume no longer needs to attract additional investors and is likely to cease reporting to the database. While the first reason implies that poorly performing funds stop reporting, which would introduce a positive survivorship bias, the second reason, which is more likely to occur in the case of good performing funds, would create exactly the opposite effect. The literature suggests that the first effect dominates and the survivorship bias amounts to 3% annually (see e.g. Fung and Hsieh (2000)).[22] Overall, our *Regression Sample* displays a probability of funds no longer reporting in the subsequent three year period amounting to 22.67%, which at first sight appears to be fairly high. Compared to the annual drop out rates for offshore hedge funds of 20% reported by Brown et al. (1999) and of 15% found in an earlier study by Brown et al. (1997), the three year drop out rate in our sample seems to be on the low end of the spectrum.

Table 5 reports the transition probabilities for the subsequent period calculated with the Carhart (1997) (Panel A), the Fung and Hsieh (1997) (Panel B), the Fung and Hsieh (2004) (Panel C), the Lhabitant (2001) (Panel D) and our SOM-based model (Panel E). If the Alphas calculated with the different performance attribution models were pure white noise, we would expect funds which ended up in one particular quartile in period t to have an equal probability of being ranked in any of the four quartiles in the subsequent period. Given the drop out rate of 22.67% the expected probability of a fund ending up in any of the four quartiles would in this case be 19.33%. We can see that for all models the probability of a fund staying in the same quartile is well above this 19.33% barrier despite one case (Fung and Hsieh (1997) model: Funds ranked in the 4^{th} quartile). But only with the SOM-based model we get the desired result that funds, which do not leave the database, will most likely stay in the same

[22] Despite those two possibilities of a fund leaving the database there are also some other reasons like mergers or name changes, which do not have an obvious effect on the sign of the survivorship bias.

quartile in the next subperiod.[23] Moreover, we can see that the probability of funds exiting the database in the next subperiod significantly decreases from hedge funds ranked in the fourth quartile to funds ranked in the second quartile for all models but the Fung and Hsieh (1997) model. Hedge funds ranked in the first quartile, however, display a drop out probability, which is always higher than the corresponding probability of funds ranked in the second quartile. A possible explanation would be that funds of the first quartile that cease reporting come primarily from the group of hedge funds which do not need further publicity and only in a few cases get liquidated because of their poor recent performance.

[Insert Table 5 about here]

In a second step we use all 146 funds, which feature Alphas for all four three-year-subperiods, to analyze the transition probabilities over longer time horizons. Tables 6, 7 and 8 show these long term transition probabilities for the five analyzed performance attribution models. It is obvious that this sample, which is conditioned on a long return history plus survival, has different properties than the full *Regression Sample* of 1,000 funds analyzed before. For example, the average Alpha of this four-period sample is according to the SOM-based model 0.17% per month higher than the average of the entire sample, which indicates a 2% annual survivorship bias. Therefore, the resulting transition probabilities draw a slightly differentiated picture.

[Insert Tables 6, 7 and 8 about here]

Over this longer time period it becomes evident that the models of Carhart (1997), Fung and Hsieh (1997) and Fung and Hsieh (2004) do not provide a long term investor with useful information. In almost all cases it is more likely that a hedge fund will end up in another quartile than staying within the same (see Panel A and B of table 6 and Panel A of table 7). Only the two models relying on actual hedge fund data (Lhabitant (2001) and our SOM-based model) provide the investor with valuable information over this long time horizon.

[23] The last column of table 5 shows whether the transition probabilities are significantly different from an equal distribution.

While the SOM-based model does an excellent job at identifying poorly performing hedge funds (see Panel D of table 8) funds initially ranked in quartile two show a tendency to move into quartile three. In the case of the Lhabitant (2001) model the probability of the weakest performing funds of staying in the fourth quartile is as high as the probability of jumping into the first quartile. Overall the long-term transition probabilities clearly underscore the value of the SOM-based model for the investor. Despite the Lhabitant (2001) model all competing performance attribution models seem to have some predictive power for the next tree year subperiod, which might be caused by some sort of momentum effect, but do not really detect a manager's investment skill, which can be seen from the random long-term transition probabilities.

The detection of persistent excess returns can have two possible reasons. The first explanation is that a manager's investment skill is important in the hedge fund business. Therefore an expert of a particular trading strategy is able to consistently outperform his peers and thereby creates a persistently positive Alpha. For the mutual fund universe Carhart (1997) finds "only very slight evidence consistent with skilled or informed mutual fund managers".[24] Another possible explanation for persistent Alphas is a misspecification of the employed performance attribution model, which measures the Alpha in all four subperiods (cf. Carhart (1997), p.80). Since persistence is detected with the two models based on hedge fund indices, which do not use theoretically constructed risk factors but investable benchmarks[25], we deem a misspecification unlikely.

5.2 Do Fund of Funds create a significant Alpha?

Single strategy hedge funds are normally run by one or two managers. Investors, however, might be interested in hedge funds as superior return vehicles on the one hand, while at the same time striving to reduce portfolio risk by entrusting their money to a larger group of decision makers and thereby diversifying across hedge fund styles. This can be achieved by either forming a private portfolio of hedge funds or by investing into a fund of hedge funds

[24] cf. Carhart (1997), p. 80.
[25] The exact replication of the hedge fund indices might fail due to the inclusion of closed funds.

(FOF). Establishing a private portfolio of hedge funds requires a considerable amount of money due to the high minimum investment requirements of most hedge funds. Investing in a fund of funds means that the the investor commits the portfolio decision to a FOF manager who is likely to be better informed but will charge fees for his services.

We use our SOM-based model as well as the other presented performance attribution models to analyze wether funds of hedge funds can make up for their additional fees[26] by entrusting the money to exceptionally gifted single strategy hedge fund managers. For this purpose we compare the average Alpha of all single strategy hedge fund in the *Regression Sample* with the average Alpha of the 541 funds of hedge funds in the *FOF Sample*. Table 9 presents the results of this analysis. We can see that according to all used performance attribution models the funds of hedge funds produce a lower average Alpha than the single strategy hedge funds, which is statistically significant at the 1 % level in all cases. The Lhabitant (2001) and our SOM-based model even report an average Alpha for the FOF category that is significantly smaller than zero (see third line of Panel B in table 9). These figures clearly show that most fund of funds managers produce an excess return, which is considerably smaller than the fees they charge. Therefore an informed investor should rather buy a self-selected portfolio of single strategy hedge funds than to rely on the ability of the average fund of funds manager.

[Insert Table 9 about here]

Finally we want to mention the high explanatory power (median R^2 of 0.61) of our SOM-based benchmarks for the *FOF Sample*. Funds of hedge funds, as the name suggests, invest in single strategy hedge funds. The hedge funds of the CISDM database account for a significant part of the investment universe open to fund of hedge funds managers, which explains why our SOM-based benchmarks achieve very high R^2s. Figure 5 depicts the entire distribution of the resulting R^2s.

[Insert Figure 5 about here]

[26] On average, the 541 funds of hedge funds in our *SOM Sample* feature a 1% management fee and a 20% performance fee.

6 Conclusion

In this paper, we present a new approach for evaluating the performance of hedge funds, which relies on a classical multi-factor model in the tradition of Sharpe's (1992) asset class factor model, but features neural network derived hedge fund benchmarks. We use the Self-Organizing Map (SOM) algorithm, which is a neural network particularly suitable for cluster analysis, to group hedge funds into homogenous style-consistent categories. By classifying the hedge funds based on their monthly return histories, we are able to identify homogenous hedge fund classes, which are not influenced by the well-known problem of faulty self-classification. We use all hedge funds contained in a specific investment style cluster to construct benchmark indices, which capture the features of the underlying dynamic trading strategies. These SOM-based benchmark indices allow us to use a simple linear regression framework for performance measurement in the hedge fund universe while still allowing for non-linearities in the analysis via the "dynamics" embedded in the regressors. Moreover these SOM-based hedge fund indices reduce the problem of omitted risk factors encountered in other models traditionally used for performance evaluation in the hedge fund universe. We also demonstrate how the SOM-based hedge fund indices can be used to infer the level of leverage employed by individual hedge funds.

In the empirical section of this paper we show that the explanatory power of our SOM-based model exceeds all other analyzed performance attribution models in the case of our randomly chosen *Regressions Sample* comprising 1,000 funds. We also analyze the evolution of Alphas over time, in order to find out whether the analyzed performance attribution models are capable of distinguishing skilled from untalented managers. Over our twelve year sample period only the SOM-based approach and the model of Lhabitant (2001), which also uses hedge fund indices, are able to detect funds with persistent excess returns (measured by the regression's Alpha). This persistence of Alphas indicates that our SOM-based performance attribution model is able to distinguish excessive risk taking from true investment skill. But we cannot rule out that a misspecification of the two models based on hedge fund indices is the reason for the observed persistence, because the Alphas are measured with the same model in all analyzed subperiods (cf. Carhart (1997), p. 80). Anyhow the predictive power of the other analyzed models fur future Alphas is rather sobering. Therefore our SOM-based performance attribution model can contribute valuable information to the portfolio selection process of individual investors. Moreover fund of hedge funds managers could use our model for the selection of single strategy hedge funds. Our analysis of the performance of funds of hedge funds suggests that fund of hedge funds managers still have to improve considerably in this discipline. All tested performance measurement models lead to the conclusion that the average fund of hedge funds does not create enough excess return to compensate for the additional layer of fees.

Overall, the evidence of this article suggests that there are some skilled or better informed managers in the hedge fund business, which produce persistent excess returns over our twelve year sample period. This could be a particular feature of the hedge fund universe, because Carhart (1997) finds slightly different results for mutual funds. Furthermore our results show that funds of hedge funds charge higher fees than the value they create by selecting single strategy hedge funds.

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Self-Declared Investment Strategy	**Number of Funds**	**Mean Return** (in %)	**Std.Dev.** (in %)	**Skewness**	**Kurtosis**
Convertible Arbitrage	149	1.0020	1.6020	0.0462	5.5984
Distressed Securities	83	1.0360	3.1378	-0.0500	5.5457
Equity-Hedge	833	1.1212	4.4908	0.1717	4.6491
Emerging Markets	175	1.1409	6.5463	-0.0427	5.3498
Fixed Income	91	0.7588	1.9160	-1.2314	8.6051
Managed Futures	1180	0.9136	5.3680	0.4571	4.3862
Global Macro	116	0.9627	4.5577	0.1672	4.5637
Merger Arbitrage	128	0.8560	1.8175	-0.2218	5.4464
Market Neutral	46	0.7408	2.3387	0.0281	4.1652
Sector Financial	29	1.4679	3.8773	-0.3925	5.8926
Sector Healthcare	28	2.2329	7.8693	1.3684	6.9430
Short Selling	33	0.4583	6.8112	0.0521	3.8781
Sector Technology	61	1.7283	11.0641	0.3809	4.1100
Sector Multi Sector	32	1.1463	4.7750	0.3251	4.8593
Long Only	24	1.4422	7.1947	-0.0842	4.2911
Sector Energy	10	1.9390	8.6309	0.1495	4.0591
Sector Real Estate	8	0.9819	2.9364	0.4357	4.3768
Fund of Funds	541	0.7760	2.1706	-0.0316	5.1269
Total Funds	**3567**				

Table 1: Hedge fund sample and summary statistics by self-declared investment strategy. Notes: The numbers given correspond to the monthly category means (e.g. "Mean Return" denotes the category mean of the arithmetic mean returns of the individual hedge fund time series).

	CAPM	Fama/French	Carhart	FH 1997	FH 2004	Lhabitant	SOM
Minimum	-0.0294	-0.0813	-0.1034	-0.1726	-0.3937	-0.5206	-0.6546
Q1	-0.0031	0.0059	0.0104	0.0517	0.0620	0.1183	0.1520
Median	0.0455	0.0757	0.0863	0.1518	0.1983	0.2946	0.3564
Q3	0.1905	0.2827	0.3077	0.2972	0.3333	0.4701	0.5508
Maximum	0.8907	0.9159	0.9153	0.9454	0.9273	0.9171	0.9311

Table 2: The table shows the regression performance of the CAPM, Fama and French (1993), Carhart (1997), Fung and Hsieh (1997), Fung and Hsieh (2004) and Lhabitant (2001) models and the results for our SOM derived benchmarks. The numbers given are the adjusted R^2 values. The first and last rows show the adjusted R^2 of the worst and best regression results, respectively. The rows labelled 'Q1', 'Median', and 'Q3' denote the results for the first, second and third quartile, respectively.

	Fund A	Fund B	FUND C	Fund D
Return Month 1	2.2%	2.8%	3.4%	-0.2%
Return Month 2	-0.4%	-1.1%	-1.8%	2.4%
Return Month 3	3.0%	4.0%	5.0%	-1.0%
Return Month 4	0.0%	-0.5%	-1.0%	2.0%
Return Month 5	-0.8%	-1.7%	-2.6%	2.8%
Return Month 6	2.0%	2.5%	3.0%	0.0%
Correlation with Fund A	1	1	1	-1
Monthly Mean	1.0%	1.0%	1.0%	1.0%
Monthly SD	1.6%	2.4%	3.2%	1.6%
Euclidean Distance to Fund A	0.000	0.018	0.036	0.071
Euclidean Distance to Fund B		0.000	0.018	0.089
Euclidean Distance to Fund C			0.000	0.107
Euclidean Distance to Fund D				0.000

Table 3: This table shows an example clarifying the influence of the standard deviation on the Euclidean Distance, which we use as similarity measure for the SOM algorithm. In this example there are 4 input vectors (Funds A-D), consisting of 6 monthly returns. The last seven lines display the correlation coefficient between fund A and the remaining funds, the first two central return moments and the Euclidean distances between the input vectors.

Strategy	Mean	Median	Max	Stand. Dev.
Convertible Arbitrage	3.95	2.00	50.00	7.25
Distressed Securities	1.37	1.15	3.00	0.55
Emerging Markets	1.56	1.10	10.00	1.30
Fixed Income	7.91	3.50	70.00	15.74
Currency Futures*	3.00	3.00	3.00	N.A.
Diversified Futures	2.72	1.40	30.00	5.48
Merger Arbitrage	2.45	1.30	30.00	4.35
Sector Financial	1.11	1.00	2.00	0.26
Sector Healthcare	1.24	1.10	1.60	0.24
Short Selling	1.50	1.50	3.00	0.51
Sector Technology	1.91	1.20	10.00	2.39

Table 4: Amount of leverage employed by the hedge funds in our sample. The categories correspond to the clusters identified by the SOM. The figures indicate the sum of total long plus short positions in comparison to the assets under management. A figure of 1 means that the sum of the positions taken is equal to the assets under management and therefore no leverage is employed. In addition to the mean and the median we also report the highest amount of leverage observed within the group of constituting funds and the standard deviation. (* Tentative estimate due to the low number of constituting funds with leverage information.)

	1^{st} Quartile	2^{nd} Quartile	3^{rd} Quartile	4^{th} Quartile	Ceased reporting	$p[\chi^2]$
PANEL A: Carhart (1997)						
1st Quartile	**23.60**	19.00	19.60	*24.60*	13.20	0.0058
2nd Quartile	15.83	**26.25**	22.65	24.85	10.42	0.0002
3rd Quartile	15.86	20.48	**24.30**	20.48	18.88	0.0415
4th Quartile	15.23	13.43	18.84	**21.64**	30.86	0.0002
PANEL B: Fung and Hsieh (1997)						
	1^{st} Quartile	2^{nd} Quartile	3^{rd} Quartile	4^{th} Quartile	Ceased reporting	$p[\chi^2]$
1st Quartile	**24.21**	18.11	12.00	20.63	25.05	0.0001
2nd Quartile	14.59	**22.83**	*23.68*	19.03	19.87	0.0334
3rd Quartile	14.19	22.03	**29.03**	19.92	14.83	0.0000
4th Quartile	*24.68*	17.93	14.77	**18.99**	23.63	0.0096
PANEL C: Fung and Hsieh (2004)						
	1^{st} Quartile	2^{nd} Quartile	3^{rd} Quartile	4^{th} Quartile	Ceased reporting	$p[\chi^2]$
1st Quartile	**25.31**	17.01	19.09	23.03	15.56	0.0032
2nd Quartile	13.39	**24.48**	*27.20*	23.64	11.30	0.0000
3rd Quartile	15.66	21.92	**24.43**	19.62	18.37	0.0288
4th Quartile	16.46	12.50	11.67	**24.58**	34.79	0.0000
PANEL D: Lhabitant (2001) (CSFB/Tremont Indices)						
	1^{st} Quartile	2^{nd} Quartile	3^{rd} Quartile	4^{th} Quartile	Ceased reporting	$p[\chi^2]$
1st Quartile	**21.26**	16.70	16.70	*21.69*	23.64	0.1968
2nd Quartile	15.25	**28.76**	23.97	16.56	15.47	0.0000
3rd Quartile	17.65	18.52	**23.09**	18.95	21.79	0.1769
4th Quartile	17.57	14.75	16.92	**22.99**	27.77	0.0191
PANEL E: SOM-based Benchmarks						
	1^{st} Quartile	2^{nd} Quartile	3^{rd} Quartile	4^{th} Quartile	Ceased reporting	$p[\chi^2]$
1st Quartile	**22.03**	17.18	18.50	19.16	23.13	0.5561
2nd Quartile	15.01	**26.49**	25.17	16.11	17.22	0.0000
3rd Quartile	17.70	18.58	**21.90**	19.03	22.79	0.6766
4th Quartile	21.59	15.42	13.88	**21.59**	27.53	0.0013

Table 5: Transition probabilities (in %) of hedge funds ranked according to their Alpha for the subsequent period. Rows indicate the ranking in the previous period, whereas columns give the ranking in the subsequent period. Hence, the first row shows the transition probabilities of funds that were ranked in the first quartile in the previous period for the subsequent period. The column labelled $p[\chi^2]$ gives the p-value of the χ^2 Goodness-of-Fit test assuming an equal distribution.

	PANEL A: Carhart (1997)						**PANEL B: Fung and Hsieh (1997)**				
	Transition probabilities of 1^{st} Quartile hedge funds.						Transition probabilities of 1^{st} Quartile hedge funds.				
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$		1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	**28.26**	13.04	13.04	45.65	0.0040	t+1	**25.64**	30.77	15.38	28.21	0.5462
t+2	**26.09**	17.39	30.43	26.09	0.6476	t+2	**30.77**	28.21	17.95	23.08	0.6793
t+3	**26.09**	26.09	23.91	23.91	0.9934	t+3	**28.21**	30.77	23.08	17.95	0.6793
Aver.	**26.81**	18.84	22.46	31.88	0.1546	Aver.	**28.21**	29.91	18.80	23.08	0.3104
	Transition probabilities of 2^{nd} Quartile hedge funds.						Transition probabilities of 2^{nd} Quartile hedge funds.				
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$		1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	23.91	**17.39**	30.43	28.26	0.6093	t+1	25.64	**20.51**	28.21	25.64	0.9217
t+2	32.61	**30.43**	21.74	15.22	0.3124	t+2	23.08	**17.95**	30.77	28.21	0.6793
t+3	32.61	**21.74**	21.74	23.91	0.6873	t+3	20.51	**20.51**	20.51	38.46	0.2875
Aver.	29.71	**23.19**	24.64	22.46	0.6219	Aver.	23.08	**19.66**	26.50	30.77	0.3660
	Transition probabilities of 3^{rd} Quartile hedge funds.						Transition probabilities of 3^{rd} Quartile hedge funds.				
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$		1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	17.39	43.48	**26.09**	13.04	0.0186	t+1	23.08	25.64	**35.90**	15.38	0.3395
t+2	21.74	28.26	**17.39**	32.61	0.4714	t+2	12.82	43.59	**30.77**	12.82	0.0145
t+3	13.04	19.57	**36.96**	30.43	0.0959	t+3	10.26	25.64	**38.46**	25.64	0.1009
Aver.	17.39	30.43	**26.81**	25.36	0.1707	Aver.	15.38	31.62	**35.04**	17.95	0.0038
	Transition probabilities of 4^{th} Quartile hedge funds.						Transition probabilities of 4^{th} Quartile hedge funds.				
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$		1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	30.43	26.09	30.43	**13.04**	0.2910	t+1	25.64	23.08	20.51	**30.77**	0.8260
t+2	19.57	23.91	30.43	**26.09**	0.7697	t+2	33.33	10.26	20.51	**35.90**	0.0843
t+3	28.26	32.61	17.39	**21.74**	0.4714	t+3	41.03	23.08	17.95	**17.95**	0.1319
Aver.	26.09	27.54	26.09	**20.29**	0.6347	Aver.	33.33	18.80	19.66	**28.21**	0.0764

Table 6: Transition probabilities (in %) of hedge funds ranked according to their Alpha at time t for the next three periods. The column labelled $p[\chi^2]$ gives the p-value of the χ^2 Goodness-of-Fit test assuming an equal distribution.

PANEL A: Fung and Hsieh (2004)

Transition probabilities of 1^{st} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	**23.81**	11.90	30.95	33.33	0.1979
t+2	**26.19**	28.57	21.43	23.81	0.9241
t+3	**23.81**	26.19	26.19	23.81	0.9924
Aver.	**24.60**	22.22	26.19	26.98	0.8810
	29.91	18.80	23.08	0.3104	
Transition probabilities of 2^{nd} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	24.39	**26.83**	21.95	26.83	0.9659
t+2	29.27	**19.51**	31.71	19.51	0.5674
t+3	36.59	**14.63**	14.63	34.15	0.0689
Aver.	30.08	**20.33**	22.76	26.83	0.4308
Transition probabilities of 3^{rd} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	12.20	41.46	**29.27**	17.07	0.0373
t+2	17.07	29.27	**26.83**	26.83	0.6964
t+3	19.51	31.71	**36.59**	12.20	0.1058
Aver.	16.26	34.15	**30.89**	18.70	0.0092
Transition probabilities of 4^{th} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	41.46	19.51	17.07	**21.95**	0.1058
t+2	29.27	21.95	19.51	**29.27**	0.7425
t+3	21.95	26.83	21.95	**29.27**	0.8829
Aver.	30.89	22.76	19.51	**26.83**	0.3078

PANEL B: Lhabitant (2001)

Transition probabilities of 1^{st} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	**29.73**	21.62	21.62	27.03	0.8662
t+2	**24.32**	18.92	18.92	37.84	0.3155
t+3	**40.54**	24.32	10.81	24.32	0.0870
Aver.	**31.53**	21.62	17.12	29.73	0.1044
Transition probabilities of 2^{nd} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	21.62	**32.43**	24.32	21.62	0.7621
t+2	18.92	**37.84**	21.62	21.62	0.3443
t+3	18.92	**35.14**	29.73	16.22	0.3155
Aver.	19.82	**35.14**	25.23	19.82	0.0736
Transition probabilities of 3^{rd} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	16.67	33.33	**25.00**	25.00	0.5724
t+2	27.78	22.22	**33.33**	16.67	0.5276
t+3	16.67	27.78	**30.56**	25.00	0.6695
Aver.	20.37	27.78	**29.63**	22.22	0.4720
Transition probabilities of 4^{th} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	32.43	13.51	27.03	**27.03**	0.4086
t+2	29.73	21.62	24.32	**24.32**	0.9159
t+3	24.32	13.51	27.03	**35.14**	0.3155
Aver.	28.83	16.22	26.13	**28.83**	0.1883

Table 7: Transition probabilities (in %) of hedge funds ranked according to their Alpha at time t for the next three periods. The column labelled $p[\chi^2]$ gives the p-value of the χ^2 Goodness-of-Fit test assuming an equal distribution.

PANEL A: Transition probabilities of 1^{st} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	**21.62**	27.03	18.92	32.43	0.6606
t+2	**35.14**	27.03	16.22	21.62	0.4086
t+3	**35.14**	16.22	27.03	21.62	0.4086
Aver.	**30.63**	23.42	20.72	25.23	0.5062
PANEL B: Transition probabilities of 2^{nd} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	19.44	**25.00**	44.44	11.11	0.0341
t+2	22.22	**22.22**	33.33	22.22	0.7212
t+3	22.22	**27.78**	30.56	19.44	0.7744
Aver.	21.30	**25.00**	36.11	17.59	0.0403
PANEL C: Transition probabilities of 3^{rd} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	25.00	30.56	**25.00**	19.44	0.8281
t+2	25.00	19.44	**33.33**	22.22	0.6695
t+3	16.67	27.78	**25.00**	30.56	0.6695
Aver.	22.22	25.93	**27.78**	24.07	0.8636
PANEL D: Transition probabilities of 4^{th} Quartile hedge funds.					
	1^{st} Qu.	2^{nd} Qu.	3^{rd} Qu.	4^{th} Qu.	$p[\chi^2]$
t+1	35.14	16.22	10.81	**37.84**	0.0444
t+2	18.92	29.73	16.22	**35.14**	0.3155
t+3	27.03	27.03	16.22	**29.73**	0.6606
Aver.	27.03	24.32	14.41	**34.23**	0.0298

Table 8: SOM-based benchmarks transition probabilities (in %) of hedge funds ranked according to their Alpha at time t for the next three periods. The column labelled $p[\chi^2]$ gives the p-value of the χ^2 Goodness-of-Fit test assuming an equal distribution.

PANEL A: *Regression Sample* (1000 hedge funds)					
Statistic	**Carhart (1997)**	**Fung/Hsieh (1997)**	**Fung/Hsieh (2004)**	**CSFB/Tremont**	**SOM Benchmarks**
average (monthly) Alpha in %	0.49	0.59	0.71	0.20	0.05
Alpha of the median fund in %	0.46	0.20	0.72	0.24	0.06
standard deviation of monthly Alphas (across funds, in %)	1.01	9.52	1.18	1.63	1.57
% of funds with Alpha > 0	76.80	56.20	84.00	60.10	53.80
% of funds with Alpha < 0	23.20	43.80	16.00	39.90	46.20
% of funds with Alpha significantly > 0	27.20	7.20	41.30	12.80	7.80
% of funds with Alpha significantly < 0	2.30	1.70	1.80	3.50	5.50
PANEL B: *FOF Sample* (541 funds of hedge funds)					
Statistic	**Carhart (1997)**	**Fung/Hsieh (1997)**	**Fung/Hsieh (2004)**	**CSFB/Tremont**	**SOM Benchmarks**
average (monthly) Alpha in %	0.21	-0.25	0.55	-0.09	-0.16
$p[\mu_{\alpha_{FOF}} < \mu_{\alpha_{RS}}]$	1.0000	0.9930	0.9997	1.0000	0.9998
$p[\mu_{\alpha_{FOF}} < 0]$	0.0000	0.9352	0.0000	0.9994	1.0000
Alpha of the median fund in %	0.23	0.07	0.57	-0.02	-0.13
standard deviation of monthly Alphas (across funds, in %)	0.61	3.87	0.60	0.67	0.69
% of funds with Alpha > 0	75.42	53.42	90.94	47.13	35.86
% of funds with Alpha < 0	24.58	46.58	9.06	52.87	64.14
% of funds with Alpha significantly > 0	35.86	8.50	63.77	9.98	5.36
% of funds with Alpha significantly < 0	2.40	2.59	1.29	12.01	14.97

Table 9: Alpha comparison between the *Regression Sample* and the *FOF Sample* in the period from May 1992 to April 2004. Panel A shows the results for five different performance attribution models applied to the *Regression Sample*, whereas Panel B gives the results of the same models for the *FOF Sample*. Results given in the last two line of each panel are significant at the 5% level. The second and third line of Panel B show the p-values of a one sided t test on the equality of means. The second line has the alternative hypothesis of $\mu_{\alpha_{FOF}} < \mu_{\alpha_{RS}}$ and the third line assume the alternative hypothesis of $\mu_{\alpha_{FOF}} < 0$.

	CA	**DS**	**EM**	**FI**	**MA**	**SF**	**SH**	**SS**	**ST**	**FUC**	**FUD**
CA	1	0.4012	0.2526	0.3134	0.3639	0.1471	0.1513	-0.1007	0.2487	0.019	-0.102
		(0)	*(0.0046)*	*(0.0004)*	*(0)*	*(0.1031)*	*(0.0934)*	*(0.2656)*	*(0.0053)*	*(0.8341)*	*(0.2596)*
DS		1	0.5032	0.1595	0.6214	0.4437	0.4342	-0.6471	0.688	-0.0289	-0.2516
			(0)	*(0.0768)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0.7502)*	*(0.0048)*
EM			1	0.1251	0.3439	0.5007	0.2155	-0.3986	0.3835	-0.0591	-0.1921
				(0.1662)	*(0.0001)*	*(0)*	*(0.0163)*	*(0)*	*(0)*	*(0.5142)*	*(0.0326)*
FI				1	0.0045	0.0134	-0.0077	0.0493	-0.0528	-0.0292	-0.0188
					(0.9604)	*(0.8826)*	*(0.9324)*	*(0.5866)*	*(0.56)*	*(0.7477)*	*(0.8354)*
MA					1	0.4389	0.3323	-0.3636	0.4742	0.0085	-0.2058
						(0)	*(0.0002)*	*(0)*	*(0)*	*(0.9257)*	*(0.0218)*
SF						1	-0.0208	-0.3573	0.2585	0.0645	-0.0821
							(0.8187)	*(0)*	*(0.0037)*	*(0.4766)*	*(0.3646)*
SH							1	-0.6042	0.6956	-0.1093	-0.1014
								(0)	*(0)*	*(0.227)*	*(0.2623)*
SS								1	-0.8543	0.1492	0.1873
									(0)	*(0.0982)*	*(0.0372)*
ST									1	-0.1093	-0.1926
										(0.2267)	*(0.0321)*
FUC										1	0.6426
											(0)
FUD											1

Table 10: Correlation matrix of the SOM derived benchmark indices. (Note: p-values are given in parentheses.)

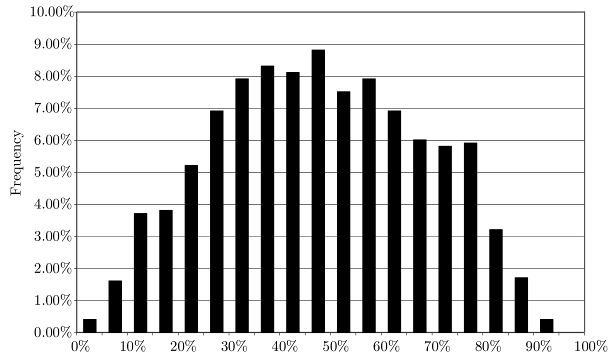

Figure 1: Distribution of R^2 obtained from regressing the 1,000 hedge funds of the *Regression Sample* on the Neural Network (SOM) derived Benchmarks.

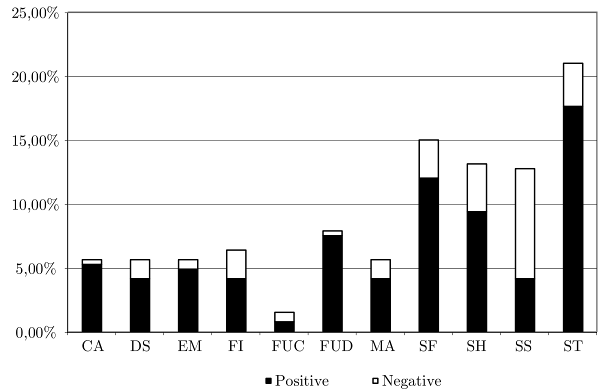

Figure 2: Percentage of regressions in which a particular SOM-based strategy benchmark is the most significant regressor for self-declared equity hedge funds.

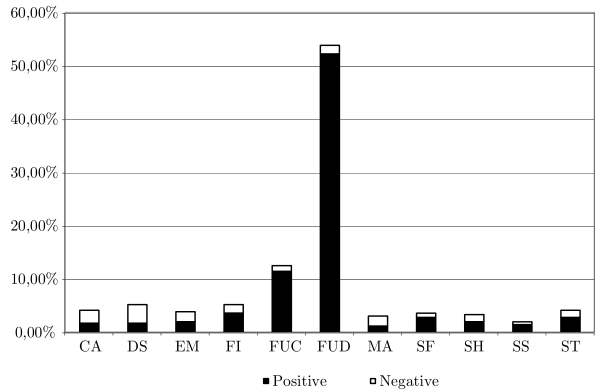

Figure 3: Percentage of regressions in which a particular SOM-based strategy benchmark is the most significant regressor for self-declared managed future funds.

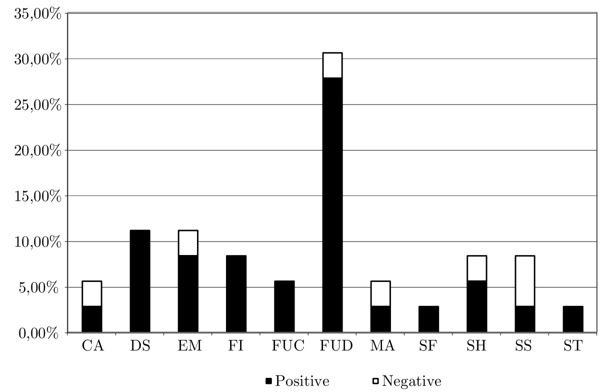

Figure 4: Percentage of regressions in which a particular SOM-based strategy benchmark is the most significant regressor for self-declared global macro funds.

Notes: The black sections in the bars of figures 2-4 indicate positive regression coefficients, whereas the white sections represent negative regression coefficients. The abbreviations represent the following strategy benchmarks: CA (convertible arbitrage), DS (distressed securities), EM (emerging markets), FI (fixed income), FUC (currency futures), FUD (diversified futures), MA (merger arbitrage), SF (sector financial), SH (sector healthcare), SS (short selling) and ST (sector technology).

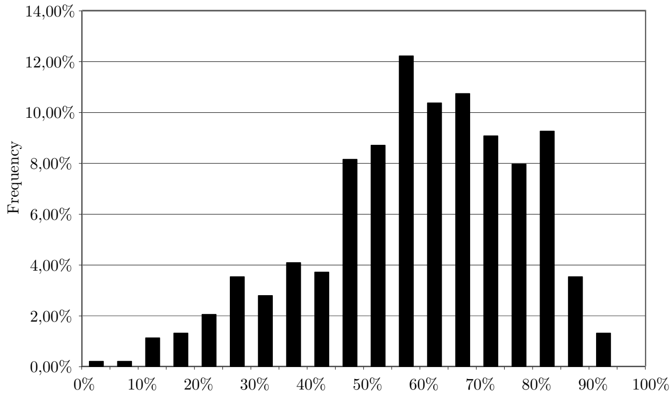

Figure 5: Distribution of R^2 for fund of hedge funds regressed against the SOM-based strategy benchmarks.