Hedge fund performance, classification with machine learning, and managerial implications*

Emmanouil Platanakis[¥]

Dimitrios Stafylas[€]

Charles Sutcliffe[£]

Wenke Zhang[©]

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¥ School of Management, University of Bath, Bath, BA2 7AY, England. Email: E.Platanakis@bath.ac.uk

€ School for Business and Society, University of York, York, YO10 5GD, England. Email: dimitrios.stafylas@york.ac.uk

£ The ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6DL, England. Email: c.m.s.sutcliffe@reading.ac.uk

© School of Management, University of Bath, Bath, BA2 7AY, England. Email: wz798@bath.ac.uk

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Abstract

Prior academic research on hedge funds focuses predominately on fund strategies in relation to market timing, stock picking, and performance persistence, among others. However, the hedge fund industry lacks a universal classification scheme for strategies, leading to subjective fund classifications and inaccurate expectations of hedge fund performance. This study uses machine learning techniques to address this issue. First, it examines whether the reported fund strategies are consistent with their performance. Second, it examines the potential impact of hedge fund classification on managerial decision making. Our results suggest that for most reported strategies there is no alignment with fund performance. Classification matters in terms of abnormal returns and risk exposures, although the market factor remains the most important exposure for hedge funds. An important policy implication of our study is that the classification of hedge funds affects asset and portfolio allocation decisions, and the construction of the benchmarks against which performance is judged.

Keywords: Hedge funds; classification; machine learning; alternative investments

JEL Classification Numbers: C38; C58; G23

Introduction

During the last decade hedge funds have received significant attention, not only from academic researchers, but also from practitioners. As of the first quarter of 2023, the total assets under management (AUM) for the hedge fund industry was almost USD$5.0 trillion (BarclayHedge, 2023). Each hedge fund declares its investment strategy, which is both advertised to potential investors and used by databases when reporting hedge fund performance.[1] Investors seek to achieve a diversified portfolio when making asset allocation decisions, which rely on the expected risk and return of possible investments and their correlations with each other. The formation of these expectations for hedge funds is heavily influenced by the reported past performance of the different hedge fund strategies supplied by the available databases (e.g. Avramov et al. 2013; Agarwal et al. 2017; Karehnke and Roon, 2022). Therefore, the classification of hedge funds into particular strategies by databases has an important influence on investment decisions.

While databases generally classify hedge funds according to the strategy declared by the hedge fund itself, hedge funds sometimes diverge from, adjust, or cease to follow their declared strategy. In consequence, such hedge funds are classified by the databases to an inappropriate strategy. Since performance differs as between strategies, this leads to investors forming inaccurate expectations about hedge fund performance, and prevents them from forming portfolios that match their objectives. As there is no universal classification scheme for hedge fund strategies, database vendors employ

[1] Due to the private partnership nature of hedge funds, information disclosure is not regulated by the Securities and Exchange Commission (SEC), and the inclusion of a hedge fund in a database is a voluntary decision taken by its managers. This can lead to history bias, as only the more successful hedge fund managers are motivated to report their performance. Even if a fund manager decides to report their performance, this could be limited to only one database. Hence, hedge fund data is both biased, patchy and fragmented, which constitutes a major issue for researchers and investors.

different classifications when forming hedge fund indices; leading to differences between indices complied by different databases that claim to measure the same strategy. This was documented by Amenc and Martellini (2003), who showed that indices for the same strategy have very low correlations. This inconsistency has an impact on investment decisions and performance against benchmarks.

Studies have analyzed the investment attractiveness of hedge fund indices (Brooks and Kat, 2002), the survivorship and selection biases of hedge fund indices (Fung and Hsieh, 2002) and the measurement and interpretation issues of hedge fund indices (Brittain, 2001; Schneeweis, et al. 2002; Stafylas et al. 2017). However, the use of inconsistent indices or benchmarks constitutes a challenge for finance managers and investors because they lead to ambiguous performance rankings (Dybvig and Ross, 1984; Dahlquist and Soderlind, 1999). Although the hedge fund literature is vast, there is only limited research on fund classification and its implications for financial decision-making and asset and portfolio allocation. Our study addresses this lacuna.

The limited research related to the classification of hedge funds and its importance for investors' decisions serves as the main motivation of our paper. We shed light on the following questions: (*i*) Does hedge fund classification vary according to specific performance features (risk and return characteristics)? (*ii*) If yes, does this have any economic significance and policy implications for finance managers and investors? To the best of our knowledge, we are the first to examine these classification issues when evaluating hedge fund performance in terms of excess (abnormal) returns and exposures. Using data from *Morningstar*, and exploiting machine learning techniques, we examine and classify hedge funds into different strategies based on their risk and return characteristics.[2] We use machine learning techniques to classify hedge funds into ten clusters, depending on their specific features. Then we analyze the performance of these clusters in terms of their excess returns (*Jensen's* alpha) and systematic exposures using various asset pricing models. We then compare them to ten broad strategies based on the strategies reported by database vendors.

The main findings of our research include the following: (*i*) our results indicate that the classification of hedge funds by databases has only a modest relationship with risk and return; (*ii*) there are differences in excess returns and exposures between funds within the broad reported strategies, and the clusters based on performance features; (*iii*) for both the broad reported strategies and our classification based on performance features, the market factor remains the most important risk exposure; (*iv*) a few strategies (e.g., S*ystematic Futures* and *Volatility Funds*) are more homogeneous than other strategies.

We make several important contributions to the hedge fund literature, with implications for financial decisions and policy making. First, using machine learning techniques, we investigate the accuracy of the classification of hedge funds into broad strategies by the funds themselves and the data providers. Contrary to previous studies, where the grouping or strategy classification of hedge funds is mostly based on the subjective views of database vendors or researchers, we apply a statistically-based clustering approach that uses each fund's return and risk characteristics. Second, we compare the performance of the broad strategies used by database vendors and the previous literature with that of our clustered strategies. We do this by employing widely used empirical asset pricing models to analyse hedge fund performance in terms of

[2] Morningstar is widely used in academic studies in empirical finance and hedge funds (see among others Prather and Middleton, 2006; Baibing et al. 2017; and Cui et al. 2019). Morningstar contains both live and dead funds.

excess returns and systematic exposure. Our findings will help investors to classify hedge funds into strategies that are exposed to the same risk factors, and therefore have a similar expected performance. This has implications for asset allocation by hedge fund investors.

The rest of the article is organized as follows. The next section presents the related literature and the hypothesis development. Section three presents our data and methodology. The fourth section presents our results and discussion, and the fifth section concludes.

Literature Review and Hypotheses

Our work is centred around agency theory and information asymmetry. The former examines the impact of the conflict of interest between agents and principals, for instance, managers and shareholders (see Jensen and Smith, 1985) or bondholders and stockholders (Smith and Warner, 1979) among others. In our study, the relationship between investors and fund managers fits into this framework and combined with the information asymmetry (see Noe, 1988; Brennan and Hughes, 1991; Nachman and Noe, 1994), they can shed light on fund managers' behaviour when they report funds' strategy and performance, having better and more timely information compared to investors.

It is well known in the investment performance literature that inefficient benchmarks can result to misleading assessments (Dybvig and Ross, 1984; Dahlquist and Soderlind, 1999), due to the joint hypothesis testing problem (Li et al. 2016). The classification of hedge funds and the selection of the relevant benchmark is a non-trivial process for investors and finance managers. However, in investment practice and the academic literature, the strategy reported by hedge funds is taken for granted. For instance, when examining hedge fund performance and systematic exposure, authors such as Getmansky (2004), Bali, et al. (2011), Chen et al. (2021), Osinga et al. (2021), Kuvandikov et al. (2022) and Karehnke and Roon (2022) use the classification scheme of the databases. Jawadi and Khanniche (2012), Meligkotsidou and Vrontos (2014) and Ferland and Lalancette (2021) use hedge fund indices provided by databases.[3] Other authors, such as Capocci and Hubner (2004), Patton and Ramadorai (2013), Joenvaara and Kosowski (2021), and Liang et al. (2022), use more than one database, and perform a mapping between the hedge fund strategies provided by the databases.[4] Other authors, such as Agarwal, et al. (2004) and Kosowski, et al. (2007), map their data into broader classifications - directional, relative value, security selection and multi-process funds. Bares, et al. (2003) use a classification based on the asset class, investment process and geographical region provided by the fund manager.

Although important, previous studies do not question the validity of the hedge fund strategy classifications employed by databases. This issue can have a significant impact on managerial decision making with respect to the performance evaluation[5] of pension funds, endowment funds and other institutional investors. This is an important issue, as most institutional investors have policies related to the type and category of financial assets in which they are prepared to invest, particularly their riskiness. It is common knowledge that hedge funds have the flexibility to change their investment style without changing their declared strategy[6], and a few strategies such as *Global*

[3] Indices suffer from problems such as hedge fund representativeness and other biases. For instance, indices may not be directly investable, and when a fund ceases reporting, it is usually excluded from the underlying index. Databases also have different criteria when including a fund in their indices.

[4] Because the same strategies have different descriptions, e.g. relative value vs convertible arbitrage, event driven vs distressed securities, macro vs global macro; the mapping process involves grouping similar strategies into a single (broad) strategy.

[5] In terms of abnormal returns (Jensen's alpha) and risk exposure.

[6] There is an information asymmetry and agency theory conflict of interest between fund managers and investors.

Macro and *Multi-Strategy* are not well defined or easily replicated. Hence, hedge fund indices used as benchmarks for hedge fund performance, might well be unsuitable for sound financial decision making.

There are a few studies that examine strategy distinctiveness and fund performance using hedge fund indices. For instance, Panopoulou and Voulelatos, (2017) show that fund managers who deviate most from their peers, have higher systematic and idiosyncratic risk without offering sufficiently higher returns. Similarly, Sun et al. (2012) found a negative relationship between strategy distinctiveness and subsequent performance. It is noticeable that both studies rely on prior literature classifications of hedge funds (e.g., Joenvaara et al. 2019; Brown and Goetzmann, 1997, 2003).[7]

Overall, existing hedge fund classification practices are problematic for investors, database vendors and researchers. In their initial prospectus, hedge fund managers may claim they follow a certain strategy, but later switch to another strategy when running their funds without publicizing this change in strategy. There is a strong need for a universally agreed way of classifying hedge funds into particular strategy groups. Mappings based on the information published by hedge funds can be subjective and, if not performed with appropriate due diligence, produce misleading results. We address the issue of this potential subjectivity. Based on the foregoing discussion, our hypothesis related to the accuracy of strategy classification is as follows:

H1: *Reported hedge fund strategies are determined by specific features that describe the fund's characteristics.*

[7] These classifications were hedge fund indices of declared strategies.

In the academic literature there are many studies that deal with hedge funds' dynamic nature in terms of their exposure and returns (e.g., Bali, et al. 2011; Giannikis and Vrontos, 2011; Chen et al. 2021), changes in their asset and portfolio allocations (e.g. Patton and Ramadorai, 2013; Ferland and Lalancette, 2021) and significant exposure to specific factors (e.g. Meligkotsidou and Vrontos, 2014;). These studies find common risk factors such as the market, commodities and credit are shared by many fund strategies. Factors related to the default spread and VIX are also economically important (Avramov et al., 2013); and studies, e.g., Bali et al. (2011, 2014), find that macro-economic risk factors, such as the default spread, term spread, short-term interest rates, equity market index, inflation rate and unemployment rate are powerful determinants of hedge fund returns. Other studies, such as Racicot and Theoret (2016), Agarwal, et al. (2017), and Stafylas et al. (2018) use macroeconomic variables and market uncertainty to explain hedge fund returns over time. Investor sentiment or market psychology also has an important role in explaining hedge fund returns (see Kellard, et al. 2017; Zheng, at al., 2018; Osinga et al. 2021), as fund managers adjust the exposure of their portfolios to changes in market sentiment. Lastly, another branch of the literature examines the timing ability of hedge funds (Chen and Liang, 2007; Cai and Liang, 2012; Cao et al., 2013), showing that fund managers have timing skills.[8] Almost all previous studies examining different aspects of hedge fund performance[9],

[8] Finally, other studies such as Bollen and Whaley (2009), Billio et al. (2012), and O'Doherty et al. (2015) consider methodological issues and structural breaks in hedge fund returns via the use of advanced econometric methods. They show that funds' risk factors change over time, and that funds who can switch their exposure over time, outperform their peers.

[9] For example, cross-sectional variations in returns in relation to market-related risk factors (Fung and Hsieh, 1997, 2001, and 2004; Agarwal and Naik, 2003), macroeconomic variables (Avramov et al. 2013; Bali et al. 2014; Racicot and Theoret, 2016; Stafylas et al. 2018), persistence (Banquero et al. 2005; Stulz, 2007; Jagannathan et al. 2010) or as portfolio diversifiers (Danvir and Hutson, 2006; Eling, 2009; Platanakis et al. 2019; Newton et al. 2021).

take as given the reported classification of the funds. Hence, many conclusions and managerial decisions may be based on inconsistent and misleading classifications.

Despite the fact that the hedge fund literature is enormous in terms of examining fund performance, fund characteristics, fund managers' skills, etc., there has been no examination of how hedge fund strategies can be determined objectively from return data, rather than relying on statements by hedge fund managers. There is also the problem that the data for such a statistical analysis of hedge funds comes from many different databases. We suggest a statistical approach which uses hedge fund returns, and their features e.g., mean return, standard deviation, skewness, and kurtosis. Practitioners can then use the resulting hedge fund classification to develop and revise their portfolio allocation strategies and policies. Consequently, our second hypothesis concerning the impact of classification on managerial decision making is proposed below:

H2: *Hedge fund classification based on the first four moments of hedge fund returns has the potential to improve investment decision making.*

Data and Methodology

We analyse the *Morningstar* database, which contains both live and dead funds, and is one of the most widely used in the hedge fund literature. The inclusion of dead funds addresses the problem of survivorship bias. As most hedge fund databases came into existence in the early to mid-1990s, we consider net-of-fees monthly returns from January 1995 to August 2021. Similar to Ibbotson et al. (2011), Bali et al. (2011), Stafylas et al. (2018), and Chen et al. (2021), we exclude the first 12 monthly returns to minimize instant history bias. Other studies, such as Ackermann et al. (1999) exclude the first 24 or more returns; however the exclusion of more returns can lead to truncated database bias. The initial sample consists of 20 reported strategies of North American hedge funds, with no funds of funds. We aggregate the 20 strategies into ten broad strategies based on strategy descriptions from various sources; e.g. *Morningstar* and the classifications of other authors such as Baibing et al. 2017; Cui et al. 2019.[10] To avoid our results being dominated by large funds, the total returns for each strategy and broad hedge fund strategies are the equally weighted mean returns of the funds involved.

Table 1, Panel A presents the correlation matrix for the ten broad hedge fund strategies. The highest (lowest) correlation is between the *Equity* and *Event* (*Debt* and C*urrency*) broad strategies at 0.836 (-0.022). The *Currency* strategy has a low correlation with most hedge fund broad strategies, as does the *Systematic Futures* strategy. Overall, most broad strategies have modest correlations that are statistically significant at the 5% level. Panel B, reports the summary statistics for each of the ten broad hedge fund strategies. *Equity* and *Systematic Futures* provide the highest mean returns, and are also among the highest standard deviations. Using the *Jarque-Bera* test we reject the normality of returns on the ten broad strategies at the 1% level.

Insert Table 1 around here

We use three machine learning methods - support vector machines (SVM), random forests, and *K*-means clustering. The first two are supervised learning, as they are trained on a back history of observations and the corresponding actual classifications. SVMs separate the observations based on their distance from a hyperplane, while

[10] For instance, similar funds investing or exploiting debt such as debt arbitrage, long-only debt, or long/short debt constitute a broad strategy called debt. Funds that focus on equity investing such as long-only equity, equity market neutral etc constitute the equity broad strategy. Other strategies that exploit pricing inefficiencies that may occur before or after a corporate or news event such as merger arbitrage, convertible arbitrage, distressed securities etc form the event-driven broad strategy, and so on. Strategies such as systematic futures, and currency that have a clear distinction from other strategies, form the Systematic futures, and Currency broad strategies, respectively.

random forests use an ensemble of decision trees to solve the classification problem. These two types of machine learning are suitable for our research as both work well in classifying observations, even when the number of observations is limited. The third machine learning method, *K*-means clustering, can be used as either supervised or unsupervised learning, making it suitable for situations where the back history lacks actual classifications, with classification based on a threshold distance.[11] The following sections contain details of each method; followed by the empirical asset pricing models we use for hedge fund performance evaluation.

Support Vector Machines

A support vector machine (SVM) is a supervised machine learning model that computes either linear or non-linear boundaries between two classes. It finds the hyperplane that maximises the distance from it to the nearest observation on each side (the margin). For multi-dimensional tasks that cannot be linearly separated, a SVM transforms the input data into a higher dimensional space by kernel functions that make the input data linearly separable.

In a classification setting, given a training set (x_k, y_k) $(k = 1, 2, \dots n)$ with a binary response $y_k \in \{-1, 1\}^n$, $w^\top x_k + b$ denotes the hyperplane that separates the sample data by maximizing the margin, w denotes a vector of coefficients of the input variables, and b is the intercept. The distance (margin) of each point from the hyperplane is computed as:

$$\frac{y_k(w^\top x_k + b)}{\|w\|_2} \tag{1}$$

[11] Supervised machine learning methods can model the original classification of hedge funds based on the subjective strategy choices of a database. To model the classification of hedge funds using their actual performance we need to use unsupervised machine learning, regardless of any prior knowledge of strategy definitions.

where $\| w \|_2$ is the ℓ_2 norm, i.e., $\| w \|_2 := \sqrt{w_1^2 + \cdots + w_n^2}$. The optimal classification model that maximizes the margin is obtained by solving the following quadratic optimization problem:

$$\min \| \mathbf{w} \|_2^2 \quad (2)$$

$$s.t.\ y_k(w^\top x_k + b) \geq 1 \ \ \forall\, k = 1, \cdots n \quad (3)$$

$$w \in \mathbb{R}^p, b \in \mathbb{R} \quad (4)$$

However, when the sample cannot be linearly separated, slack variables are introduced, leading to the following formulation (Cortes and Vapnik, 1995):

$$min_{\xi,w,b} \ \| \boldsymbol{w} \|_2^2 + C \sum_{k=1}^{n} \xi_k^2 \quad (5)$$

$$\text{s.t.}\ \ y_k(w^\top x_k + b) \geq 1 - \xi_k,\ \ k = 1, \dots n \quad (6)$$

$$\xi_k \geq 0,\ \ k = 1, \dots n \quad (7)$$

where ξ_k is the slack (error) variable for observation k, and C is a tuning weight that defines the trade-off between the minimization of the error and the maximization of the margin, with larger values of C representing a higher penalty for misclassification.

For more complex problems of multi-classification, the data can be mapped to a higher dimensional space through a mapping function $\Phi(x_k)$, which allows for linear classification in the new feature space. Based on the mapping function, the kernel function $K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$ $(i, j = 1, 2, \dots n)$ is introduced for solving the quadratic programming problem, such that

$$\min \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_i \alpha_i \alpha_j K(X_i, X_j) - \sum_{j=1}^{n} \alpha_j \quad (8)$$

$$\text{s.t.}\ \sum_{i=1}^{n} y_i \alpha_i = 0,\ \ \forall\, i = 1, \cdots n \quad (9)$$

$$0 \leq \alpha_i \leq C,\ \ \forall\, i = 1, \cdots n \quad (10)$$

Commonly used kernel functions include the polynomial, sigmoid, and Gaussian kernels. In this approach, SVM identifies the hyperplane that separates every pair of classes, neglecting observations in the other classes.

Random Forests

Random forests (RF) is an ensemble method based on multiple decision trees. It uses bagging to generate many new training sets, which it uses to form different decision trees to separate the training set into classes. To classify new observations, RF selects the class indicated by the majority of the decision trees. By combining the predictions of multiple decision trees RF has a better performance than a single classifier. RF also improves the performance of each decision tree by artificially restricting the set of features considered for each recursive split. The advantage of RF is its capability to capture complex data interactions with a relatively low bias if the tree grows sufficiently deep. RF is less prone to the overfitting problem, and generally achieves a superior performance to decision trees.

Suppose there are N observations. The process of generating a RF starts by creating B bootstrap samples from the training data, where each sample consists of $n < N$ randomly chosen observations from the training set, with replacement. Then random decision trees T_b $(b = 1, 2, \ldots B)$ grow by randomly selecting m variables, picking the best variable among them, and splitting the node into two sub-nodes. This process is repeated for the two sub-nodes, until the minimum node size is reached. To predict with new data x, the regression function of the b_{th} RF tree is:

$$\hat{f}_{\mathrm{rf}}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{11}$$

In the regression, the RF model does not explicitly represent the error term and constant term in the mathematical equation. Instead, it implicitly incorporates them in the ensemble of decision trees $T_b(x)$ that constitute the model. The main objective of this model is to minimize the error between the predicted and actual values of the dependent variable by generating a diversified set of decision trees that can make precise predictions. The constant term of each decision tree $T_b(x)$ is the average of the dependent variable values of the training samples that fall within the leaf nodes. The error term for each decision tree $T_b(x)$ is the difference between the predicted and actual values of the dependent variable for each sample in the training set. The final error term for the RF regression model is the average of the error terms for all the decision trees in the forest.

For classification, the RF model identifies the best results by majority voting, which assigns a sample on the basis of the most frequent class assignment. The RF classification $\hat{C}_{\mathrm{rf}}^{B}(x)$ is formulated as:

$$\hat{C}_{\mathrm{rf}}^{B}(x) = \textit{majority vote}\left\{\hat{C}_b(x)\right\}_1^B \tag{12}$$

K-means Clustering

K-means clustering is one of the most commonly used unsupervised machine learning methods for partitioning a given data set into *K* groups, where *K* is pre-determined. Observations are classified by calculating the distance to the group centroids. The fundamental idea of *K*-means clustering is to minimize the within-cluster variation, which is defined as the sum of the squared Euclidean distance between each observation and its centroid. Formally, the distance function is as follows:

$$D(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2 \tag{13}$$

where x_i $(i = 1, 2 \dots n)$ is an observation belonging to cluster C_k $(k = 1, 2 \dots n)$; and μ_k is the mean value of observations assigned to cluster C_k.The total within-cluster variance is the aggregation of the sum of squared distances in each cluster. It indicates the goodness of model performance, where a smaller value indicates a more accurate result. Formally, it is defined as follows:

$$T(C) = \sum_{k=1}^{n} D(C_k) = \sum_{k=1}^{n} \sum_{x_i \in C_k} (x_i - \mu_k)^2 \quad (14)$$

The first step of *K*-means clustering is to choose the number of clusters *K*. Then, the centroid of each cluster is randomly selected, and each observation is assigned to the closest cluster centroid. The centroid is updated by calculating the new mean of all the observations in the cluster iteratively to minimize the within-cluster variance. The iteration stops when the centroid and observations of the newly formed cluster stop changing.

Asset Pricing Models

We consider three empirical asset pricing models to obtain the alphas and factor betas for the broad strategies and clusters - (*i*) Carhart's four-factor momentum model (FF4) (Carhart, 1997), (*ii*) Fama and French's five-factor model (FF5) (Fama and French, 2015), and (*iii*) Fung and Hsieh's seven-factor model (FH7) (Fung and Hsieh, 2004).[12] More specifically, we apply the following models:

$$\text{FF4: } R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + \delta_i MOM_t + e_{it} \quad (15)$$

$$\text{FF5: } R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (16)$$

$$\text{FH7: } R_{it} - R_{Ft} = \alpha_i + \eta_i PTFSBD_t + \kappa_i PTFSFX_t + \rho_i PTFSCOM_t + b_i SP500_t + s_i SIZESPR_t + \gamma_i \Delta BOND_t + \theta_i \Delta CRSPR_t + e_{it} \quad (17)$$

[12] The underlying factors of these models have been widely used, not only in financial economics, but in the hedge fund literature (see among others, Carhart, 1997; Fung and Hsieh, 2004; Capocci, 2009; Stafylas et al. 2017).

where R_{it} is the month *t* return on one of the portfolios from a classification of hedge of funds; R_{Ft} is the risk-free rate (three-month Treasury bills); R_{Mt} is the return on a value weighted market index; $(R_{Mt} - R_{Ft})$ is the market risk premium; and SMB_t (small minus big) and HML_t (high minus low) are the size and value factors, respectively. RMW_t (robust minus weak) is the profitability factor; CMA_t (conservative minus aggressive) is the investment factor, and RMW_t is the difference between returns on diversified portfolios of stocks with robust and weak profitability. More details of the construction of these portfolios can be found in Fama and French (2015).

$PTFSBD_t$ is the return on a bond lookback straddle; $PTFSFX_t$ is the return on a currency lookback straddle; $PTFSCOM_t$ is the return on a commodity lookback straddle; $SP500_t$ is the return on the S&P500 index; $SIZESPR_t$ is the return difference between the Russell 2000 and S&P500 indices; $\Delta BOND_t$ is the change in the yield of 10-year bonds; $\Delta CRSPR_t$ is the change in the difference between the *Baa* corporate bond yield and the 10-year Treasury bond yield; and α_i is the alpha of the fund (selectivity skill) after controlling for the underlying risk factors. The coefficients to be estimated are b_i, s_i, h_i and δ_i for models (1) and (2); r_i and c_i for model (2) κ_i $\eta_{i,}$, ρ_i, γ_i and θ_i for model (3), and e_{it} is the error term. We apply the three machine learning models and (a) compare the classification of hedge funds into strategies by hedge funds and data providers with their classification using past performance; and (b) examine the impact of different classifications on hedge fund abnormal returns (alpha) and factor exposures.

Results and Discussion

First, we test our hypothesis (*H1*) and examine whether the reported hedge fund strategies are consistent with hedge fund performance. Second, we investigate the economic significance of our results for fund managers and investors, and test our second hypothesis (*H2*) regarding the potential impact of classification on managerial decision making via its effect on abnormal returns and factor exposures.

Classification

The key features we use to describe the performance of hedge funds are the mean, variance, skewness and kurtosis of returns. To eliminate the influence of different magnitudes and units, we standardise these four variables so that they are suitable for comparative evaluation.

We investigate whether the 20 hedge fund strategies used by Morningstar[13] (see **Table 2**) are determined by fund performance. If so, this supports hypothesis *H1*, which has the implication that there should be few significant correlations between returns on the different hedge fund strategies. However, Table 1 shows that almost three-quarters of these correlations are significantly different from zero. We apply the three machine learning methods using four features (e.g., mean return, risk, skewness and kurtosis) as the input variables, and the 20 labels (strategies) as the corresponding output to assess whether hedge funds are classified in the same way as Morningstar. We use RF, which is efficient in dealing with redundant information, and the least affected by data quality when compared to the other two machine learning methods. According to the rule of thumb, 75% of the sample is used for training the model, with the remaining

[13] The broad strategies are those used in the academic literature based on vendors' strategy descriptions (e.g., Morningstar, Eurekahedge, etc) and other authors' classifications (such as Baibing et al. 2017; Cui et al. 2019) using similar databases.

observations used for testing. After learning from the training, only 34% of the RF classifications agreed with those of Morningstar. For robustness we also used SVM, and this produced the same classification as Morningstar for 30% of the hedge funds. Therefore, the error rates (one minus accuracy) are 66% for RF and 70% for SVM. This implies that the reported classification of two-thirds of the hedge funds differs from that based on hedge fund performance. Therefore, hypothesis *H1* does not hold for the 20 hedge fund strategies.

Insert Table 2 around here

Following the low level of agreement between the two supervised machine learning methods and Morningstar, we applied unsupervised *K*-means clustering to classifying the hedge funds, and compared the results with the ten broad strategies, i.e., we set $K = 10$[14] (see the next section). *K*-means clustering is efficient at non-linear classification, and suitable for large data sets compared to other clustering models such as hierarchy clustering.

In **Table 3** we present the proportion of hedge funds in each Morningstar strategy that is classified to each of the 10 *K*-means clusters using supervised learning. The *Long-Only Equity* (LOE) and *U.S. Small Cap Long/Short Equity* (SLSE) account for large proportions of *K*-means clusters 1, 2, 3, 4, 6, 8 and 9, and 1, 3, 4, 7, 8 and 9 respectively.

Insert Table 3 around here

We also classify the individual funds directly regardless of any prior knowledge of the 20 strategy classifications, i.e., unsupervised learning using *K*-means clustering. To avoid the influence of inconsistent time periods across individual funds, we calculate

[14] *K* was set to 10 to have the same number of broad strategies for comparison reasons.

the features based on the whole period when the fund was active. We exclude hedge funds with missing information, which leaves 1,250 hedge funds. **Table 4** shows the number of individual funds in each of the new clusters, and the first column shows their original Morningstar label. To confirm our findings in Table 3, we use the results in Table 4 to calculate the Adjusted Rand Index (ARI) (Hubert & Arabie, 1985) between the original Morningstar labels and the predicted labels of the individual hedge funds.

The ARI measures the similarity between two clusterings taking into account the differences in the number of clusters by adjusting for chance agreement. The general form of the ARI is

$$\frac{Rand\ Index - E(Rand\ Index)}{Max(Rand\ Index) - E(Rand\ Index)}$$

Rand Index (RI) is the number of similar assignments of point-pairs normalized by the total number of point-pairs, as follows:

$$\text{RI} = (\alpha + \beta)/\binom{N}{2}$$

where α is the number of times a pair of elements belongs to the same cluster across two clustering results, β is the number of times a pair of elements belongs to different clusters across two clustering results; and $\binom{N}{2}$ is the number of unordered pairs in a set of elements. $E(Rand\ Index)$ is the expected value of the RI under a null hypothesis of random clustering, which calculates the probability that two randomly assigned data points will be assigned to the same cluster in both clusterings or to different clusters in both clusterings. $Max(Rand\ Index)$ is the maximum possible value of the RI, which is achieved when the two clustering solutions are identical. The range of ARI is from -1 to 1, where 1 indicates that all data points are assigned to the same clusters in both solutions, 0 means two clustering solutions are no more similar than random chance and independent of each other, and -1 indicates all data points are assigned to different clusters in both solutions.

The value of ARI is 0.0397, which is very low; suggesting that the original strategies are inadequate for hedge fund classification based on the four characteristics of fund performance. This clustering result supports our earlier finding using RF and SVM, that hypothesis *H1* is not valid. Therefore, to the extent that hedge funds are following their declared strategy, their strategy is a poor guide to performance, which raises questions about the usefulness of the reported strategies.

Insert Table 4 around here

Performance

In order to examine our second hypothesis *H2* regarding managerial decision making, we employ three of the most prevalent asset pricing models (FF4, FF5, and FH7), and compare the abnormal returns and systematic risk of the 10 broad hedge fund strategies, and those formed by *K*-means clustering using fund performance. With the market as the most important factor, our findings are consistent with previous studies regarding the exposures of trend-following funds (Fung and Hsieh, 2004), and exposure to various factors (Agarwal and Naik, 2003; Meligkotsidou and Vrontos, 2014; Fama and French, 2015; Stafylas et al. 2018).

Table 5 presents the results using the FF4 model. All 10 broad strategies deliver statistically significant excess returns at the 5% level, or higher. The highest excess return is for *Systematic Futures* at 0.76% (*t*-statistic = 3.497), and the lowest is for *Long Only* at 0.262% (*t*-statistic = 2.263). All but *Systematic Futures* and *Currency* have a statistically significant exposure to the market factor. Three of the strategies have a significant exposure to size (SMB) or momentum (MOM), and four have a significant exposure to book-to-market capitalization (HML).

Insert Table 5 around here

When using the FF5 model, our results in **Table 6** show that all 10 broad strategies have a significantly positive constant, and that *Systematic Futures* (*Long Only*) continues to deliver the highest (lowest) excess returns to investors equal to 0.703% (0.287%). The profitability (RMW) and investment (CMA) factors are significant once, and the small minus big (SMB) and/or high minus low (HML) factors are significant for fours strategies. The market factor (MKT_RF) continues to be significant for eight strategies. As for the FF4 model, *Systematic Futures*, *Volatility* and *Currency* have very low R^2 values; and *Equity* has the highest R^2.

Insert Table 6 around here

As **Table 7** shows, there are similar results in terms of excess returns when using the FH7 model, with all ten constants being significantly positive. Returns on the S&P500 index (SP500) have a significant positive co-efficient for eight strategies, and the credit spread factor (ΔCRSPR) also has a significant negative co-efficient for eight strategies. The regressions for three strategies (*Multi Strategy, Systematic Futures* and *Macro*) have four significant factors. *Equity* still has a high R^2, while the low R^2 values for *Systematic Futures*, and *Currency* have increased.

Insert Table 7 around here

Table 8 has our results when applying *K*-means clustering based on hedge fund performance measures for the FF4 model. All but clusters 2, 5 and 7 provide excess returns to investors, ranging from 0.319 (*t*-statistic = 3.455) to 1.362 (*t*-statistic =

7.640). Cluster 2 has a particularly low R^2 (0.037) with an *F-stat* (0.838) which indicates that the FF4 model does not explain this cluster's returns. This is also the case with other clusters, such as clusters 5 and 6. Overall, the most common exposure is to the market factor.

Insert Table 8 around here

Table 9 provides the results for the FF5 model in relation to the *K*-means clusters. All but clusters 2, 5 and 7 provide statistically significant excess returns to investors. The highest is from cluster 8 at 1.389 (*t*-statistic = 7.809), and the lowest is from cluster 3 at 0.280 (*t*-statistic = 4.384). The most common exposure is the market factor, followed by the SMB. Significance of the other factors (e.g., HML, RMW, and CMA) is less common.

Insert Table 9 around here

Table 10 has the results of applying the FH7 model to the *K*-means clusters. All but clusters 2, 5, 7 provide statistically significant excess returns to investors. The highest is from cluster 8 at 1.372 (*t*-statistic = 7.622), and the lowest is from cluster 3 at 0.405 (*t*-statistic = 7.545). The particularly low R^2 (0.062) and *Prob (F-stat)* (0.939) shows that the underlying model cannot explain cluster 2 returns. Cluster 9 has statistically significant positive coefficients for PTFSBD at 0.012 (*t*-statistic = 2.003), PTFSFX at 0.019 (*t*-statistic = 3.388), PTFSCOM at 0.024 (*t*-statistic = 3.365), SP500 at 0.342 (*t*-statistic = 14.322), and SIZESPR at 0.179 (*t*-statistic = 5.917). CRSPR has a significantly negative coefficient at 0.052 (*t*-statistic = -2.999). The bond-oriented risk factors (ΔBOND and ΔCRSPR) have statistically significant negative coefficients for clusters 1, 4, 6, 7 and 10. The equity-oriented risk factors (SP500 and SIZESPR) have statistically significant coefficients for clusters 1, 3, 9, and 10.

Insert Table 10 around here

Managerial Implications

The classification of hedge funds based either on performance (return) features or on reported broad strategies has implications for the portfolio construction process when using hedge funds as portfolio diversifiers (see Platanakis et al. 2019; Newton et al. 2021), and when dealing with different client profiles. We show that, especially for portfolio construction classification studies (e.g., Chen at al. 2021), classification matters when assessing the likely future performance of stand-alone hedge funds, and when hedge funds are used as portfolio diversifiers.

We examine the potential impact of hedge fund classification on managerial decisions by examining the abnormal returns and factor exposures of hedge funds classified by their performance, and by hedge fund databases. Using the FF4 model, there are three clusters in both Tables 5 and 8 with the same four significant coefficients (constant, Market, SMB and HML) – *Equity*, *Event Driven* and *Multi-Strategy* in Table 5, and clusters 3, 4 and 10 in Table 8. This leaves six strategies in Table 5 which do not match any strategy in Table 8 in terms of their significant variables. A portfolio manager looking to invest in a hedge fund that is sensitive to a particular set of factors would probably make a different decision if they use past performance, rather than reported strategy.

For the FF5 model, only the *Systematic Futures* strategy in Table 6 and cluster 6 in Table 9 have significant coefficients for just the constant and RMW. *Multi Strategy* in Table 6 has the same three significant coefficients as clusters 1 and 9 in Table 9 (constant, market and SMB), and the *Event Driven* and *Equity* strategies have the same four significant coefficients as clusters 4 and 10 in Table 9. Again, this leaves six strategies in Table 6 that do not match any of those in Table 9.

For the FH7 model, none of the strategies in Table 7 have the same significant coefficients as those in Table 10, suggesting that all ten reported classifications have different factor sensitivities from the clusters based on performance.

Across Tables 5 to 10, regardless of the asset pricing model, there is evidence that hedge fund indices formed using reported strategies have different performance and factor sensitivities from those formed using machine learning using past performance. This supports hypothesis 2 (*H2*) that reported strategies are a poor guide to performance, and classification using machine learning applied to the first four moments of hedge fund returns is superior.

With the market as the most important factor, our findings are consistent with previous studies regarding the exposures of trend following funds (Fung and Hsieh, 2004), and exposure to various other factors (Agarwal and Naik, 2003; Meligkotsidou and Vrontos, 2014; Fama and French, 2015; Stafylas et al. 2018). We document that, especially for portfolio construction classification studies (e.g., Chen at al. 2021), the classification matters when evaluating the performance of standalone funds, or as diversifies of broader portfolios. The hedge fund classification approach can be applied and have an impact when dealing with funds as a portfolio diversifier (see Platanakis et al. 2019; Newton et al. 2021), or when dealing with different client profiles.

Conclusions

In this study we investigate whether the hedge fund classifications used by databases produce strategy classes that are homogenous in terms of risk and return. We use three machine learning methods – support vector machines, random forests and *K*-means clustering to test whether the reported hedge fund classifications correspond to classifications based on hedge fund performance (the first four moments of returns).

We find considerable differences between the rival classifications, with two-thirds of hedge funds assigned to a different strategy. This suggests that the database classifications are not very helpful for investors when building their portfolios, and that there may be more useful classifications.

We also examined the economic significance of our finding of major differences between the reported hedge fund classifications and classifications based on performance. We compared the performance of ten hedge fund classifications used by databases with those of our ten clusters formed using *K*-means clustering. We computed the abnormal returns and factor exposures of these two alternative classifications using the FF4, FF5 and FH7 asset pricing models of Carhart (1997), Fama and French (2015) and Fung and Hsieh (2004), respectively.

There is evidence that hedge fund indices formed using reported strategies have different market sensitivities from those formed using hedge fund performance. This finding is robust to various asset pricing models used. We also find that the market factor remains the most important risk exposure for hedge funds. A few strategies, such as *Systematic Futures* and *Volatility*, present some similarity for both classification methods.

Our study provides novel insights and a different perspective on how investors and fund of fund managers should evaluate and invest in hedge funds based on their characteristics. Hedge fund indices are used as benchmarks for measuring investment performance, and indices with a more homogeneous factor exposure may be more useful in this task. The use of machine learning allows managers to classify funds in a more objective way, which may affect their asset allocation decisions. Future research could study the application of different statistical classification techniques to hedge funds. For 20 years the Securities and Exchange Commission has required funds to have names that are not misleading, and in 2022 they considered extending this rule to cover names that refer to particular strategies (Olson, 2022).

Overall, the classification problem is a major issue, not only in investment decisions, but also in a broader management-related context; for instance, corporate finance (e.g., when comparing companies). A company's financial profile could be categorized with some objective criteria such as the mean distance, or a classification algorithm similar to our work that considers higher moments. Finally, the issue of different classifications of the same company has been successfully applied in other areas, such as business strategy classification (e.g., Hill, 1988; Kald et al. 2002; Landini et al. 2020).

Declaration of Competing Interest

None

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Table 1. Summary Statistics

In this table, Panel A, presents the correlation matrix of the ten broad hedge fund strategy returns; *t*-Statistics are presented in parentheses. Panel B presents the monthly return statistics (percentages) of the mean, median, standard deviation (SD), skewness, and kurtosis, along with their *Jarque-Bera* tests for normality for each broad strategy.

	Num of funds	*Debt*	*Equity*	*Event Driven*	*Multi-strategy*	*Systematic Futures*	*Volatility*	*Macro*	*Currency*	*Long Only*	*Others*
Panel A: Correlation Matrix											
Debt	248	1.000									
Equity	387	0.403	1.000								
		(7.864)									
Event	177	0.462	0.836	1.000							
		(9.302)	(27.167)								
Multi-strategy	137	0.379	0.756	0.794	1.000						
		(7.300)	(20.623)	(23.297)							
Systematic Futures	155	-0.029	0.013	-0.023	0.099	1.000					
		(-0.520)	(0.225)	(-0.418)	(1.787)						
Volatility	38	0.192	0.344	0.284	0.336	0.082	1.000				
		(2.796)	(5.241)	(4.238)	(5.101)	(1.168)					
Macro	85	0.139	0.362	0.333	0.378	0.464	0.067	1.000			
		(2.503)	(6.914)	(6.291)	(7.275)	(9.342)	(0.965)				
Currency	17	-0.022	0.012	0.013	0.039	0.585	-0.217	0.314	1.000		
		(-0.408)	(0.211)	(0.225)	(0.688)	(12.862)	(-3.171)	(5.904)			
Long Only	32	0.305	0.533	0.564	0.512	0.325	0.249	0.566	0.130	1.000	
		(5.713)	(11.242)	(12.171)	(10.634)	(6.128)	(3.683)	(12.248)	(2.339)		
Others	78	0.389	0.720	0.788	0.754	-0.031	0.228	0.395	-0.028	0.549	1.000
		(5.268)	(12.970)	(15.981)	(14.322)	(-0.384)	(2.922)	(5.371)	(-0.346)	(8.209)	
Panel B: Summary Statistics											
Mean		0.920	1.144	0.838	0.842	1.048	0.774	0.995	0.826	0.699	0.695
Median		0.825	1.337	0.943	1.002	0.718	0.859	0.734	0.464	0.747	0.723
SD of		2.701	2.933	2.135	1.591	3.856	2.642	2.439	3.165	2.342	2.220
Skewness		7.285	-0.714	-1.526	-1.620	0.548	-0.751	0.259	1.292	-0.359	-0.830
Kurtosis		117.436	6.310	12.141	12.115	3.944	2.589	4.090	6.969	5.135	11.876
Jarque-		177410.4	173.324	1238.317	1247.693	27.881	72.513	19.719	299.094	67.248	536.815
Probability		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2: Hedge Fund Strategies

This table shows the symbols of the twenty strategies and the number of observations reported in each strategy

Strategy	Symbol	Number of Observations
Debt Arbitrage	DEA	298
Long-Only Debt	LOD	428
Long/Short Debt	LSD	1300
Bear Market Equity	BME	45
Long-Only Equity	LOE	734
Equity Market Neutral	EMN	530
U.S. Long/Short Equity	LSE	2653
U.S. Small Cap Long/Short Equity	SLSE	815
Event Driven	EVD	992
Distressed Securities	DIS	354
Convertible Arbitrage	COA	547
Diversified Arbitrage	DIA	167
Merger Arbitrage	MEA	392
Multistrategy	MUY	1356
Systematic Futures	SYF	2103
Volatility	VOY	293
Global Macro	GLM	1052
Currency	CUY	195
Long-Only Other	LOO	261
No Names	NON	197

Table 3: The Clustering and Proportions of 20 Hedge Fund Strategies

This table shows the proportion of hedge funds in each new cluster using supervised learning. The odd columns show the reported classifications (symbols) of the hedge funds in each new cluster. The even columns show the proportions of hedge funds in each original strategy classified to each new cluster.

C1	Proportion of Funds	C2	Proportion of Funds	C3	Proportion of Funds	C4	Proportion of Funds	C5	Proportion of Funds	C6	Proportion of Funds	C7	Proportion of Funds	C8	Proportion of Funds	C9	Proportion of Funds	C10	Proportion of Funds
LOE	17.57%	LOE	2.30%	LOE	11.31%	LOE	1.23%	MEA	77.55%	LOE	0.54%	SYF	30.43%	LOE	7.36%	LOE	25.60%	VOY	32.08%
SLSE	17.18%	BME	2.20%	SLSE	7.61%	SLSE	1.10%	DIA	76.65%	LSD	0.23%	SLSE	23.80%	SYF	5.33%	LSE	23.20%	DEA	14.77%
SYF	15.55%	COA	2.20%	VOY	7.51%	GLM	0.86%	COA	75.14%	SYF	0.10%	LOO	23.37%	SLSE	5.15%	SLSE	20.50%	MEA	12.76%
GLM	11.41%	LSD	1.20%	EVD	6.65%	NON	0.51%	LOD	73.83%			CUY	22.56%	DIS	4.80%	EVD	17.40%	LSD	12.00%
LSE	11.12%	GLM	0.70%	GLM	5.61%	LSE	0.45%	DEA	73.49%			LOE	21.80%	GLM	4.37%	SYF	17.30%	LOD	9.35%
EVD	8.47%	SLSE	0.60%	SYF	4.90%	VOY	0.34%	EMN	73.21%			GLM	19.68%	LSE	3.05%	LOO	16.10%	GLM	8.08%
CUY	7.69%	NON	0.50%	LSE	4.82%	LSD	0.31%	LSD	70.77%			LSE	19.41%	EVD	3.02%	GLM	14.60%	DIS	7.91%
DIS	5.65%	VOY	0.30%	DIS	3.95%	DIS	0.28%	BME	68.89%			EVD	16.53%	BME	2.22%	DIS	14.40%	MUY	7.89%
COA	5.12%	LSE	0.30%	NON	3.05%	MUY	0.22%	NON	62.44%			NON	16.24%	DIA	1.20%	MUY	13.20%	LOO	7.28%
MUY	3.39%	SYF	0.30%	MUY	2.88%	EMN	0.19%	MUY	58.55%			BME	15.56%	LOD	1.17%	EMN	10.20%	CUY	6.67%
EMN	3.02%	DIS	0.30%	CUY	2.05%	SYF	0.14%	CUY	50.77%			DIS	14.97%	MUY	0.96%	NON	10.20%	BME	6.67%
DIA	2.40%	MUY	0.20%	COA	2.01%	EVD	0.10%	LOO	49.04%			MUY	12.68%	LSD	0.85%	CUY	9.70%	DIA	6.59%
LSD	2.31%			LOO	1.53%			DIS	47.74%			VOY	7.85%	VOY	0.68%	VOY	7.80%	COA	6.40%
LOO	2.30%			EMN	1.51%			VOY	43.00%			EMN	6.60%	DEA	0.67%	LOD	7.20%	EVD	6.35%
LOD	2.10%			LSD	1.38%			EVD	41.43%			LOD	5.37%	CUY	0.51%	DIA	7.20%	NON	5.08%
NON	2.03%			DEA	1.34%			GLM	34.70%			LSD	5.31%	LOO	0.38%	COA	6.60%	EMN	4.91%
DEA	1.34%			DIA	1.20%			LSE	32.76%			DIA	4.79%	EMN	0.38%	DEA	6.00%	LSE	4.82%
MEA	1.02%			MEA	1.02%			SYF	22.49%			MEA	3.32%	COA	0.18%	LSD	5.70%	SYF	3.52%
VOY	0.34%			LOD	0.93%			SLSE	21.84%			COA	2.38%	NON		BME	4.40%	SLSE	2.21%
								LOE	10.08%			DEA	2.35%	MEA		MEA	4.30%	LOE	2.18%

Table 4: The Number of Individual Funds in Each Cluster

This table shows the relationship between the 20 Morningstar strategies and the 10 new clusters formed using unsupervised *K*-means clustering. The sums are the total number of funds in each cluster.

Morningstar Strategy	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Convertible Arbitrage	2		3	6				1	3	23
Currency	5		1	1					5	1
Debt Arbitrage	1		1	5			12		5	3
Distressed Securities	14		3		7			1	4	
Diversified Arbitrage	8		1						1	3
Equity Market Neutral	25		8					1	11	3
Event Driven	26		16	1	1			4	10	9
Global Macro	40		5	1			1	8	23	3
Long-Only Debt	33		16	4			2	3	9	7
Long-Only Equity	25		27						16	3
Long-Only Other	9		6	2	1			1	4	5
Long/Short Debt	26	2	29	12	2		6	9	21	30
Merger Arbitrage	2		7	2					8	4
Multistrategy	46		34	8				3	23	8
Systematic Futures	106		10	1		2		2	29	2
U.S. Long/Short Equity	98		40	5				3	39	5
U.S. Small Cap Long/Short Equity	34		4						16	3
Volatility	4		20	1			1	5	3	3
No label	18		15					1	5	1
Bear Market Equity			1	1						1
Sum	522	2	247	50	11	2	22	42	235	117

Table 5: Ten Broad Strategies – FF4

This table provides the results of the ten broad strategies in terms of alphas and exposures using the FF4 model. The risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). SMB is small minus big, HML is high minus low book-to-market capitalization, and MOM is momentum. * and ** denote significance at the 5% and 1% levels respectively. The *t*-statistics are in parentheses.

Dep. Var:	DEBT	EQUITY	EVENT DRIVEN	MULTI STRATEGY	SYSTEMATIC FUTURES	VOLATILITY	MACRO	CURRENCY	LONG ONLY	OTHERS
C	0.549**	0.493**	0.397**	0.491**	0.76**	0.479**	0.651**	0.634**	0.262*	0.306*
	(3.820)	(8.001)	(4.949)	(6.998)	(3.497)	(2.654)	(4.950)	(3.515)	(2.263)	(2.305)
MKT_RF	0.227**	0.527**	0.298**	0.186**	0.06	0.207**	0.179**	-0.024	0.283**	0.255**
	(6.582)	(35.658)	(15.476)	(11.089)	(1.153)	(4.398)	(5.673)	(-0.554)	(10.181)	(7.993)
SMB	0.044	0.285**	0.176**	0.122**	-0.053	0.023	0.046	0.042	-0.0003	0.038
	(-0.975)	(14.621)	(6.922)	(5.506)	(-0.774)	(0.288)	(1.117)	(0.739)	(-0.009)	(0.681)
HML	0.054	0.053**	0.062*	0.066**	0.082	-0.079	-0.069	0.082	0.043	-0.131**
	(1.201)	(2.719)	(2.467)	(3.015)	(1.198)	(-1.135)	(-1.679)	(1.455)	(1.172)	(-2.759)
MOM	-0.008	-0.008	-0.033	-0.009	0.169**	0.011	0.039	0.053	0.066**	-0.165**
	(-0.267)	(-0.586)	(-1.905)	(-0.629)	(3.634)	(0.249)	(1.412)	(1.373)	(2.661)	(-5.127)
R^2:	0.157	0.868	0.577	0.417	0.042	0.11	0.128	0.015	0.261	0.497
F-statistic:	14.704	515.486	107.459	56.386	3.409	6.231	11.572	1.199	27.822	37.761
Prob(F-stat):	0.000	0.000	0.000	0.000	0.009	0.000	0.000	0.311	0.000	0.000

Table 6: Ten Broad Strategies – FF5

This table provides the results of the ten broad strategies in terms of alphas and exposures using the FF5 model. The risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). SMB is small minus big, HML is high minus low book-to-market capitalization, RMW is profitability, and CMA is investment. * and ** denote significance at the 5% and 1% levels respectively. The *t*-statistics are in parentheses.

Dep. Var:	DEBT	EQUITY	EVENT DRIVEN	MULTI STRATEGY	SYSTEMATIC FUTURES	VOLATILITY	MACRO	CURRENCY	LONG ONLY	OTHERS
C	0.555**	0.509**	0.371**	0.464**	0.703**	0.451*	0.66**	0.603**	0.287*	0.343*
	(3.731)	(7.997)	(4.439)	(6.403)	(3.093)	(2.486)	(4.833)	(3.239)	(2.371)	(2.335)
MKT_RF	0.225**	0.521**	0.31**	0.199**	0.067	0.185**	0.174**	-0.011	0.261**	0.294**
	(6.085)	(32.984)	(14.963)	(11.070)	(1.184)	(4.027)	(5.149)	(-0.228)	(8.708)	(8.503)
SMB	0.041	0.274**	0.184**	0.124**	0.022	0.061	0.045	0.044	0.033	0.044
	(0.798)	(12.432)	(6.352)	(4.950)	(0.276)	(0.755)	(0.947)	(0.682)	(0.793)	(0.692)
HML	0.071	0.075**	0.080*	0.048	-0.162	-0.004	-0.115*	-0.029	0.011	-0.031
	(1.163)	(2.899)	(2.355)	(1.609)	(-1.750)	(-0.049)	(-2.068)	(-0.375)	(0.226)	(-0.555)
RMW	-0.011	-0.031	0.025	0.015	0.210*	0.154	-0.003	0.023	0.072	-0.074
	(-0.153)	(-1.046)	(0.661)	(0.449)	(2.003)	(1.385)	(-0.041)	(0.264)	(1.296)	(-0.863)
CMA	-0.025	-0.025	-0.034	0.047	0.271	-0.361**	0.08	0.216	-0.057	-0.026
	(-0.279)	(-0.638)	(-0.662)	(1.068)	(1.947)	(-2.713)	(0.954)	(1.892)	(-0.766)	(-0.249)
R^2:	0.157	0.868	0.574	0.419	0.024	0.151	0.125	0.02	0.25	0.414
F-statistic:	11.731	412.655	84.454	45.263	1.509	7.089	8.986	1.301	20.975	21.434
Prob(F-stat):	0.000	0.000	0.000	0.000	0.187	0.000	0.000	0.263	0.000	0.000

Table 7: Ten Broad Strategies – FH7

This table provides the results of the ten broad strategies in terms of alphas and exposures using the FH7 model. The risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). PTFSBD is the return on a bond lookback straddle, PTFSFX is the return on a currency lookback straddle, PTFSCOM is the return on a commodity lookback straddle, SP500 is the return on the S&P500, SIZESPR is the return difference of the Russell 2000 and the S&P500 index, ΔBond is the monthly change in the 10-year treasury security yield, and ΔCRSPR is the change in the difference between the BAA and 10-year treasury security yield. * and ** denote significance at the 5% and 1% levels respectively. The *t*-statistics are in parentheses.

Dep. Var:	DEBT	EQUITY	EVENT DRIVEN	MULTI STRATEGY	SYSTEMATIC FUTURES	VOLATILITY	MACRO	CURRENCY	LONG ONLY	OTHERS
C	0.606 * *	0.565**	0.475**	0.569**	0.866**	0.527**	0.675**	0.668**	0.348**	0.448**
	(4.350)	(9.362)	(6.616)	(9.273)	(4.300)	(2.936)	(5.317)	(4.186)	(3.089)	(3.295)
PTFSBD	-0.015	-0.004	-0.006	-0.008*	0.04**	-0.012	0.007	-0.017	-0.0004	0.006
	(-1.714)	(-1.016)	(-1.466)	(-2.089)	(3.289)	(-1.073)	(0.859)	(-1.718)	(-0.057)	(0.755)
PTFSFX	-0.006	0.004	-0.001	0.003	0.048**	-0.018	0.018*	0.082**	0.007	0.002
	(-0.795)	(1.291)	(-0.208)	(0.917)	(4.201)	(-1.649)	(2.471)	(8.938)	(1.148)	(0.225)
PTFSCOM	-0.009	-0.005	-0.008	0.001	0.043**	0.002	0.034**	-0.004	0.014	-0.018
	(-0.829)	(-1.009)	(-1.556)	(0.244)	(2.915)	(0.181)	(3.648)	(-0.371)	(1.717)	(-1.743)
SP500	0.169**	0.501**	0.251**	0.142**	0.094	0.144**	0.197**	0.016	0.241**	0.232**
	(4.955)	(33.913)	(14.258)	(9.473)	(1.899)	(2.873)	(6.330)	(0.419)	(8.723)	(6.474)
SIZESPR	0.044	0.332**	0.162**	0.096**	0.003	0.039	0.073	0.053	0.019	0.024
	(-1.008)	(17.658)	(7.259)	(5.039)	(0.043)	(0.530)	(1.854)	(1.073)	(0.544)	(0.444)
ΔBOND	-0.032	0.008	-0.019	-0.007	-0.056	-0.02	-0.028	-0.047	-0.039*	-0.003
	(-1.414)	(0.813)	(-1.636)	(-0.729)	(-1.736)	(-0.775)	(-1.354)	(-1.834)	(-2.175)	(-0.185)
ΔCRSPR	-0.083**	-0.057**	-0.110**	-0.099**	-0.091*	-0.015	-0.056*	-0.043	-0.099**	-0.082**
	(-3.324)	(-5.312)	(-8.548)	(-9.029)	(-2.528)	(-0.489)	(-2.442)	(-1.509)	(-4.914)	(-3.567)
R^2:	0.211	0.873	0.663	0.555	0.181	0.132	0.192	0.231	0.303	0.476
F-statistic:	11.929	307.319	87.685	55.579	9.82	4.303	10.577	13.378	19.4	19.461
Prob(F-stat):	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 8: *K*-Means Clusters – FF4

This table provides the results of the ten *K*-means clusters in terms of alphas and exposures using the FF4 model. The risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). SMB is small minus big, HML is high minus low book-to-market capitalization, and MOM is momentum. * and ** denote significance at the 5% and 1% levels respectively. The *t*-statistics are in parentheses.

Dep. Var:	CLUSTER_1	CLUSTER_2	CLUSTER_3	CLUSTER_4	CLUSTER_5	CLUSTER_6	CLUSTER_7	CLUSTER_8	CLUSTER_9	CLUSTER_10
C	0.505**	1.417	0.320**	0.420**	0.514	1.041**	0.080	1.362**	0.749**	0.319**
	(6.001)	(-1.592)	(5.148)	(3.088)	(-1.214)	(3.609)	(-0.451)	(7.640)	(7.249)	(3.455)
MKT_RF	0.329**	0.063	0.355**	0.171**	0.316**	-0.103	0.257**	0.010	0.316**	0.235**
	(16.316)	(-0.326)	(23.849)	(5.244)	(2.931)	(-1.485)	(5.775)	(0.231)	(12.730)	(10.619)
SMB	0.136**	-0.138	0.149**	0.129**	0.007	-0.08	0.043	0.254**	0.145**	0.091**
	(5.122)	(-0.443)	(7.578)	(2.986)	(-0.040)	(-0.875)	(-0.722)	(4.426)	(4.444)	(3.118)
HML	0.025	0.282	0.136**	0.156**	-0.105	0.077	0.178**	-0.129*	0.009	0.095**
	(0.936)	(1.079)	(6.952)	(3.646)	(-0.645)	(0.849)	(3.265)	(-2.377)	(0.264)	(3.287)
MOM	0.055**	0.217	-0.015	-0.012	-0.001	0.114	0.004	-0.059	0.011	-0.015
	(3.049)	(0.833)	(-1.144)	(-0.397)	(-0.012)	(1.845)	(0.097)	(-1.602)	(0.488)	(-0.735)
R^2:	0.537	0.037	0.741	0.171	0.055	0.033	0.186	0.096	0.436	0.362
F-statistic:	91.356	0.356	224.904	16.269	2.696	2.659	14.535	7.163	60.811	44.691
Prob(F-stat):	0.000	0.838	0.000	0.000	0.032	0.033	0.000	0.000	0.000	0.000

Table 9: *K*-Means Clusters – FF5

This table provides the results of the ten *K*-means clusters in terms of alphas and exposures using the FF5 model. The risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). SMB is small minus big, HML is high minus low book-to-market capitalization, RMW is profitability, and CMA is investment. * and ** denote significance at the 5% and 1% levels respectively. The *t*-statistics are in parentheses.

Dep. Var:	CLUSTER_1	CLUSTER_2	CLUSTER_3	CLUSTER_4	CLUSTER_5	CLUSTER_6	CLUSTER_7	CLUSTER_8	CLUSTER_9	CLUSTER_10
C	0.501**	1.695	0.280**	0.398**	0.749	0.929**	0.081	1.389**	0.759**	0.296**
	(5.697)	(1.832)	(4.384)	(2.829)	(-1.751)	(3.143)	(0.439)	(7.809)	(7.124)	(3.103)
MKT_RF	0.326**	0.045	0.369**	0.178**	0.252*	-0.087	0.245**	0.035	0.316**	0.2435**
	(14.946)	(0.213)	(23.316)	(5.089)	(2.373)	(-1.181)	(5.436)	(0.802)	(11.950)	(10.253)
SMB	0.151**	-0.399	0.173**	0.148**	-0.111	0.075	0.099	0.109	0.123**	0.107**
	(4.952)	(-0.974)	(7.791)	(3.027)	(-0.588)	(0.727)	(1.479)	(1.748)	(3.341)	(3.229)
HML	-0.044	0.377	0.126**	0.159**	0.065	-0.09	0.217**	-0.133	-0.013	0.099*
	(-1.2151)	(1.1952)	(4.8262)	(2.7812)	(0.3729)	(-0.7470)	(2.9881)	(-1.8918)	(-0.2984)	(2.5588)
RMW	0.041	-0.421	0.068*	0.051	-0.527*	0.412**	0.098	-0.286**	-0.052	0.043
	(1.001)	(-0.733)	(2.292)	(0.779)	(-2.024)	(3.004)	(1.182)	(-3.617)	(-1.049)	(0.979)
CMA	0.084	-0.336	-0.018	-0.044	-0.483	-0.063	-0.223*	0.379**	0.092	-0.034
	(1.549)	(-0.656)	(-0.447)	(-0.505)	(-1.526)	(-0.344)	(-1.996)	(3.587)	(1.403)	(-0.586)
R^2:	0.528	0.042	0.744	0.173	0.086	0.051	0.204	0.173	0.441	0.364
F-statistic:	70.279	0.316	182.726	13.165	3.519	3.346	12.978	11.257	49.608	35.917
Prob(F-stat):	0.000	0.900	0.000	0.000	0.004	0.005	0.000	0.000	0.000	0.000

Table 10: *K*-Means Clusters – FH7

This table provides the results of the ten *K*-means clusters strategies in terms of alphas and exposures using the FH7 model. The risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). PTFSBD is return of bond lookback straddle, PTFSFX is return of the currency lookback straddle, PTFSCOM is return of commodity lookback straddle, SP500 is return of the S&P500, SIZESPR is return difference of the Russel 2000 and the S&P500 index, ΔBond is monthly change of the 10-year treasury security, and ΔCRSPR is change in difference of the BAA and 10-year treasury security. * and ** denote significance at the 5% and 1% levels respectively. The *t*-statistics are in parentheses.

Dep. Var:	CLUSTER_1	CLUSTER_2	CLUSTER_3	CLUSTER_4	CLUSTER_5	CLUSTER_6	CLUSTER_7	CLUSTER_8	CLUSTER_9	CLUSTER_10
C	0.578**	1.675	0.405**	0.586**	0.733	1.113**	0.238	1.372**	0.783**	0.426**
	(7.286)	(1.719)	(7.545)	(5.303)	(1.755)	(4.019)	(1.596)	(7.622)	(8.041)	(5.707)
PTFSBD	0.007	0.007	-0.011**	-0.015*	0.02	0.037*	0.004	0.026*	0.012*	-0.007
	(1.423)	(0.187)	(-3.304)	(-2.285)	(0.822)	(2.204)	(0.473)	(2.346)	(2.003)	(-1.522)
PTFSFX	0.021**	0.018	0.002	-0.008	0.003	0.013	-0.015	0.0001	0.019**	-0.007
	(4.717)	(0.343)	(0.599)	(-1.307)	(0.125)	(0.939)	(-1.731)	(0.004)	(3.388)	(-1.737)
PTFSCOM	0.011	-0.045	-0.009*	-0.007	-0.005	-0.002	-0.016	0.007	0.024**	-0.013
	(1.851)	(-0.622)	(-2.466)	(-0.888)	(-0.174)	(-0.088)	(-1.430)	(0.558)	(3.365)	(-2.321)
SP500	0.323**	-0.192	0.304**	0.052	0.219	-0.12	0.108**	0.073	0.342**	0.158**
	(16.643)	(-0.809)	(23.126)	(1.907)	(1.921)	(-1.779)	(2.843)	(1.631)	(14.322)	(8.648)
SIZESPR	0.183**	0.004	0.15**	0.049	-0.13	-0.014	0.013	0.216**	0.179**	0.06**
	(7.428)	(0.013)	(8.987)	(1.418)	(-0.769)	(-0.158)	(0.279)	(3.759)	(5.917)	(2.603)
ΔBOND	-0.026*	-0.063	-0.001	-0.057**	0.064	-0.213**	-0.086**	0.035	-0.0003	-0.038**
	(-2.019)	(-0.602)	(-0.087)	(-3.236)	(1.095)	(-4.763)	(-3.864)	(1.283)	(-0.016)	(-3.174)
CRSPR	-0.067**	-0.155	-0.091**	-0.226**	-0.142*	-0.152**	-0.257**	0.006	-0.052**	-0.147**
	(-4.704)	(-1.106)	(-9.486)	(-11.401)	(-1.990)	(-3.067)	(-9.759)	(0.201)	(-2.999)	(-11.021)
R^2:	0.591	0.062	0.807	0.456	0.096	0.114	0.438	0.087	0.501	0.586
F-statistic:	64.308	0.321	186.369	37.381	2.783	5.667	28.079	3.651	44.702	63.075
Prob(F-stat):	0.000	0.939	0.000	0.000	0.009	0.000	0.000	0.001	0.000	0.000