An Analysis of Hedge Fund Styles using the Gap Statistic

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Abstract

The global hedge fund industry uses a system of self-classification to define investment styles. Hedge fund database providers, such as the Hennessee Group and Tremont TASS, classify funds into between 11 and 23 investment styles. In contrast, recent studies by Fung and Hsieh (1997) and Brown and Goetzmann (2003) have identified between five and eight investment styles in the hedge fund industry. Given the wide range of estimates regarding the number of styles, this study considers this problem using the Gap Statistic approach of Tibshirani, Walther and Hastie (2001), finding the presence of only three styles in the global hedge fund industry for the period 1994 through 2001. These three hedge fund styles can be described as: quasi-long equity; non-directional; and, global directional. Such a finding is controversial as it suggests that plan sponsors must carefully consider decisions to allocate plan monies to hedge funds on the basis of investment style, and, more importantly, whether hedge funds can justify the fees charged.

JEL Classification: *G1*, *G2*

Key words: *Hedge Funds*, *Investment Style*, *Gap Statistic*

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1. INTRODUCTION

One of the fastest areas of growth in funds management is the global hedge fund industry. The Securities and Exchange Commission (SEC) (2003) estimate the size of the industry at approximately $600 to $650 billion in funds under management in the United States alone.[1] Investors have developed an interest in allocating capital to hedge funds who are specialist fund managers that employ strategies which are generally not restricted to univariate equity or bond market mandates. Eichengreen and Mathieson (1998) report that some of the most popular investment hedge fund styles include: global; market neutral; and, event driven strategies.

Hedge fund providers construct their own peer-group based methodologies to self-classify their investment styles as there are no generally accepted methods to categorise these fund managers. Tremont TASS Europe Ltd (hereafter TASS) classify hedge funds into 11 categories while the Hennessee Group classify the industry into 23 different investment styles.[2] The consideration of investment style is important as hedge funds are referred to as 'alternative investments', where plan sponsors can access these funds that claim to possess different sets of return, risk and correlation metrics in comparison to traditional asset classes. The process of defining and classifying funds based on their investment style in an asset allocation process is important for a plan sponsor.

The debate in hedge fund style analysis widens further when the academic literature from Fung and Hsieh (1997) suggests the presence of only five or eight hedge fund styles, while Brown and Goetzmann (2003) estimate eight hedge fund styles. These results are in stark contrast to industry based hedge fund style categories. This study contributes to the debate of hedge fund style analysis by employing the new Tibshirani, Walther and Hastie (2001) Gap Statistic (hereafter referred as the 'Gap Statistic') to estimate the number of hedge fund investment styles. The findings from

[1] The United States (U.S.) Securities Exchange Commission (2003) expects the hedge fund industry to grow to over $1 trillion in the next five to ten years. As at 31 December 2002, the SEC (2003) valued the U.S. stock market at $11.8 trillion, making the size of the hedge fund industry in the U.S. at approximately 5% of the value of the U.S. stockmarket.

[2] Refer to www.tassresearch.com and www.hennesseegroup.com for further details.

this study are controversial as it suggests the statistical presence of only three hedge fund investment styles over the long term. This has implications for the plan sponsor as the findings suggest that the allure of hedge fund managers providing portfolio diversification opportunities needs to be tempered by the Gap Statistic's estimate of only three hedge fund investment styles which can be best described as quasi-long equity, non-directional and global directional. This study shows that when that Gap Statistic is estimated on both survivors and non-survivors, the short-term estimates of up to five styles, with the long-term Gap Statistic estimating the presence of only three hedge fund investment styles.

This remainder of the study is organised as follows. Section 2 provides a review of the literature across the disciplines of style analysis, hedge funds and the development of the Gap Statistic. Section 3 discusses the methodology employed in this study. Section 4 provides a description of the data used in the analysis. Section 5 reports the results. The conclusion discusses the findings and the implications they have on investors such as plan sponsors.

2. REVIEW OF THE LITERATURE

Investment style analysis is a relatively new area in the finance literature, yet, it has a long tradition in industry and plays an important role in both the mutual fund sector and the emerging hedge fund industry. Early mutual fund studies by Carlson (1970) and McDonald (1974) found that fund performance was related to the asset composition and the investment objectives of the fund. However, it was not until the contribution by Sharpe (1988, 1992) whereby investment style analysis was considered in a more rigorous framework. The work of Sharpe (1992) was the first regression-based approach to identifying fund style, where each factor in the model represented a return on an asset class.[3] This model is popularly referred to as the Sharpe 'returns based factor model' or 'returns based style analysis model'.[4]

[3] An earlier study by Tierney and Winston (1991) proposed a model which assigned investment styles to fund managers within the equity mutual fund domain of 'value to growth' and 'small to large' market capitalisation equity market world, which is similar to the findings of Fama and French (1992) who introduced the 'Fama-French three factor model'.

[4] The model proposed by Sharpe (1992) had a more broad application than Tierney and Winston (1991) as it was able to identify and assign investment style to fund managers, regardless of the exposures in various asset classes.

While there is a general acceptance of the Sharpe (1992) model as the dominant style analysis framework, researchers have identified weaknesses in the use of linear regression models in the modeling of dynamic portfolios. The work of Dybvig and Ross (1985), Christopherson (1995) and Buetow, Johnson and Runkle (2000) find that linear based models are inadequate in modeling dynamic portfolios. The limitation of the linear-based approach is further highlighted by diBartolomeo and Witkowski (1997) who estimated that up to 40% of mutual funds in the United States may be misclassified by employing the model of Sharpe (1992). The critique of the use of linear models in style classification of mutual funds sparked the search for an alternative investment style identification framework in order to model the dynamics of fund managers.

Motivated by the limitation of the linear framework, the work of Brown and Goetzmannn (1997) and, subsequently, Brown, Goetzmann, Hiraki, Otsuki and Shiraishi (2001), developed an alternate approach to style analysis by developing a *k*-means hard cluster analysis with a generalised least squares procedure in order to adjust for a fund's time-varying variance or heteroskedasticity. The Brown and Goetzmann (1997) methodology has three clear advantages over the linear approach. First, it is able to relax the assumption of normally distributed data. Second, the estimation of factor loadings (or style attributes) is not required under a cluster analysis, and, finally, factor loadings can change over time.[5]

The success of Brown and Goetzmann's (1997) approach to style classification in the mutual fund domain made it an obvious candidate to consider classification problems in the global hedge fund industry. However, prior to examining such an approach, it is important to acknowledge that the hedge fund industry presents additional

[5] The contribution of the Brown and Goetzmann (1997) model is important as it expresses the classic modern asset pricing model in the form of a modified *k*-means hard cluster analysis procedure. Modern asset pricing models take the mathematical form that return is equal to a conditional (group) expected return plus an idiosyncratic error. The work of Brown and Goetzmann (1997) employs a standard *k*-means cluster analysis on monthly return data, which inherently has the characteristics and styles of each fund embedded in the monthly returns. The *k*-means cluster analysis classifies data using cross sectional attributes of the data, and when the procedure is restricted to cluster solely on returns as the attribute, the Brown and Goetzmann (1997) model interprets this *k*-means cluster analysis as grouping return data based on conditional group mean returns, which is consistent with standard modern asset pricing theory. By considering this new mathematical framework, Brown and Goetzmann (1997) have developed an investment style analysis tool which is useful when the risk factors are not fully identified.

challenges to practitioners and academics seeking to classify hedge fund returns which are not normally distributed. The work of Leland (1999), Lo (2001), Fung and Hsieh (2001) and Lochoff (2002) finds that, not only do hedge fund returns violate the assumption of IID normal, but they also possess non-linear and dynamic return characteristics.

There is a paucity of industry-wide studies of style analysis of the global hedge fund industry.[6] In an attempt to reduce the dimensionality of the hedge fund style problem, the work of Fung and Hsieh (1997) conducted a principal component analysis (PCA) to build a returns-based style factor approach. Fung and Hsieh (1997) estimated five and eight principal components that explained the variation of return of hedge funds, however, the PCA model generated low levels of cross sectional variation in hedge fund returns, and a test statistic was not employed to verify their results.

In a more recent industry wide study, Brown and Goetzmann (2003) employed the Brown and Goetzmann (1997) grouping algorithm and estimated the presence of eight hedge fund investment styles by using the Quandt (1960) likelihood ratio (LR) test statistic. While the LR test is simple to use, Brown and Goetzmann (2003) acknowledge the limitations associated with this test statistic. Specifically, the LR test assumes that returns are normally distributed and there is ambiguity in the appropriate degrees of freedom in such a test. The inherent limitations of the LR test motivates this study to find a substitute to the LR test which can better estimate the number of hedge fund investment styles.

[6] For two recent style-specific studies (as distinct from industry-wide analyses) see Fung and Hsieh (2001) who examined the managed futures or trend following style, and Mitchell and Pulvino (2001) who analysed the risk/merger arbitrage investment style.

Table 1 Gap Statistic Comparison

The table compares the estimated number of groups in various datasets employing various grouping test statistics based on 50 trials. Some rows do not sum to 50 because the number of clusters chosen was greater than 10. The symbol * denotes the column to the correct number of clusters. CH refers to Calinski and Harabasz (1974), KL is Krzanowski and Lai (1985), Hartigan refers to Hartigan (1975), Silhouette is Kaufman and Rousseeuw (1990), Gap/unif is Gap Stat with uniform distribution, Gap/pc is Gap Stat with PCA.

Method	Estimates of the following numbers of cluster k:									
	1	2	3	4	5	6	7	8	9	10
Null model in 10 dimensions										
CH	0*	50	0	0	0	0	0	0	0	0
KL	0*	29	5	3	3	2	2	0	0	0
Hartigan	0*	0	1	20	21	6	0	0	0	0
Silhouette	0*	49	1	0	0	0	0	0	0	0
Gap/unif	49*	1	0	0	0	0	0	0	0	0
Gap/pc	50*	0	0	0	0	0	0	0	0	0
3-cluster model										
CH	0	0	50*	0	0	0	0	0	0	0
KL	0	0	39*	0	5	1	1	2	0	0
Hartigan	0	0	1*	8	19	13	3	3	2	1
Silhouette	0	0	50*	0	0	0	0	0	0	0
Gap/unif	1	0	49*	0	0	0	0	0	0	0
Gap/pc	2	0	48*	0	0	0	0	0	0	0
Random 4-cluster model in 3 dimensions										
CH	0	0	0	42*	8	0	0	0	0	0
KL	0	0	0	35*	5	3	3	3	0	0
Hartigan	0	1	7	3*	9	12	8	2	3	5
Silhouette	0	20	15	15*	0	0	0	0	0	0
Gap/unif	0	1	2	47*	0	0	0	0	0	0
Gap/pc	2	2	4	42*	0	0	0	0	0	0
Random 4-cluster model in 10 dimensions										
CH	0	1	4	44*	1	0	0	0	0	0
KL	0	0	0	45*	3	1	1	0	0	0
Hartigan	0	0	2	48*	0	0	0	0	0	0
Silhouette	0	13	20	16*	5	0	0	0	0	0
Gap/unif	0	0	0	50*	1	0	0	0	0	0
Gap/pc	0	0	4	46*	0	0	0	0	0	0
2 elongated clusters										
CH	0	0*	0	0	0	0	0	7	16	27
KL	0	50*	0	0	0	0	0	0	0	0
Harigan	0	0*	0	1	0	2	1	5	6	35
Gap/unif	0	0*	17	16	2	14	1	0	0	0
Gap/pc	0	50*	0	0	0	0	0	0	0	0

Source: Tibshirani, Walther and Hastie (2001), page 420, Table 1.

The search for a substitute for the LR test has emerged with the development of the Gap Statistic. This new test statistic aims to better estimate the number of groups in a dataset. The consideration of the Gap Statistic is strongly supported by tests on various datasets where it is well founded and statistically robust. Table 1 provides the results from Tibshirani *et. al.,* (2001) which compares the Gap Statistic and its competing cluster based test statistics when applied to different types of data. The central message to be taken from the table is that the Gap Statistic overcomes the long-standing problem in classification research which relates to the statistical estimation of the optimal number of groups in a dataset.[7]

The recent development of the Gap Statistic means that little research has been performed with this test statistic in the area of style classification. At the time of writing, only one paper, by Lajbcygier and Ong (2003), had considered the efficacy of this test using a sample of Japanese mutual funds. To the best of our knowledge, this is the first study to use this test statistic in the global hedge fund industry setting.[8]

3. RESEARCH METHODOLOGY

The research agenda of this study is to estimate the number of hedge fund investment styles by employing the Gap Statistic. The objective of the study is to either confirm the academic findings of five to eight styles from Fung and Hsieh (1997) and Brown and Goetzmann (2003), or to support the notion of industry based groupings of 11 to 23 hedge fund styles. The findings from this study are controversial as it estimates the presence of only three hedge fund styles which differs to academic and industry based classification estimates.

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[7] Various researchers have attempted to develop a test statistic, such as Calinski and Harabasz (1974), Krzanowski and Lai (1988) and Kaufman and Rosseeuw (1990), however, they were unable to determine if a dataset has one cluster only, that is, these test statistics could only determine the presence of two or more clusters only. Other grouping test statistics such as Quandt (1960), Wolfe (1970), Duda and Hart (1973) and Milligan and Cooper (1985) operated on the assumption that the data is random and comes from a multivariate normal distribution. These methods tend to exhibit high levels of rejecting the null hypothesis of one cluster.

[8] The Gap Statistic is a promising test statistic, however, it is not a panacea, as Ben-Hur, Elisseeff and Guyon (2002) identify its shortcoming which is its reliance on the sum of squares distance criterion, which makes it biased towards compact clusters rather than sparse data relationships. Considering the recent development of the Tibshirani *et. al.*, (2001) Gap Statistic, this study contributes to the body of knowledge of this new test statistic.

The mathematical framework employed in this study is organised as follows. First, the Brown and Goetzmann (1997) model is employed to group the hedge funds into various styles. Second, the Quandt (1960) likelihood ratio (LR) test is employed to estimate the number of hedge fund investment styles, which follows the contribution of Brown and Goetzmann (2003). Third, the Gap Statistic is employed as a substitute for the LR test and the number of hedge fund investment styles are re-estimated. This method of analysis using the Gap Statistic will provide new insights to the various investment styles that exist in the global hedge fund industry.

GSC Model

The Brown and Goetzmann (1997, 2003) grouping procedure is initially employed in this study. The Brown and Goetzmann (1997, 2003) Generalised Style Classification (GSC) model is effectively a *k*-means hard cluster analysis which clusters on monthly returns and has been modified as a generalised least squares (GLS) procedure in order to take into account the time varying and fund specific residual return variance. The GLS procedure accounts for heteroskedasticity by scaling the data observations by the inverse of the estimated standard deviation. The GLS methodology also reduces the impact that outliers may have on the classification algorithm thereby improving the results of the cluster analysis. The GSC model is the following GLS procedure for the mean of each investment style which is mathematically summarised as;[9]

$$\hat{\mu}_{I\,t}^{*} = \sum_{i \in I} \frac{R_{it}}{\mathrm{var}(\hat{e}_i)} / \sum_{i \in I} \frac{1}{\mathrm{var}(\hat{e}_i)} \tag{1}$$

where

R_{it} = the returns of fund *i* for each time period; and,

$\mathrm{var}(\hat{e}_i)$ = the time series variance of fund *i*.

The above GLS adjustment is employed to update the *k*-means centroid mean whenever a fund switches from one investment style cluster group to another. The subsequent procedure in the GSC model is the estimation of the sum of squares of each investment style *j* which is mathematically expressed as;

[9] Refer to Brown and Goetzmann (1997) for a full specification of this model.

$$SSQ_j = \sum_{t=1}^{T} \sum_{I \in I_j} \sum_{i \in I} \frac{(R_{it} - \hat{\mu}_{It}^*)^2}{\operatorname{var}(\hat{e}_i^*)\operatorname{var}(\hat{e}_t^*)} \qquad (2)$$

In order to use the Brown and Goetzmann (1997) GSC model, one must prespecify the number of styles. The test statistic employed to estimate the number of hedge fund styles in Brown and Goetzmann (2003) is the Quandt (1960) LR test.

Test Statistic 1: Quandt (1960) Likelihood Ratio (LR) Test

The GSC model requires the appropriate number of styles to be prespecified. This requirement of the GSC model led Brown and Goetzmann (1997, 2003) to employ the Quandt (1960) likelihood ratio test for *K* styles (as opposed to *K*+1 styles) and is mathematically expressed as;

$$LR = Tm\left(\ln \frac{ssq_k}{Tm} - \ln \frac{ssq_{k+1}}{Tm} \right) \qquad (3)$$

where

T	=	the number of periods;
m	=	the number of funds; and,
ssq_k and ssq_{k+1}	=	heteroskedasticity adjusted sum of squared errors.

The assumptions of the Quandt (1960) LR test used in Brown and Goetzmann (2003) is that it is approximately χ^2 distributed with 2*T* degrees of freedom. The limitations of the LR test are mentioned in Brown and Goetzmann (1997) who acknowledge the ambiguity in the appropriate degrees of freedom, the appropriateness of the χ^2 distribution, and the assumption of normally distributed returns.

Test Statistic 2: Tibshirani *et. al.*, (2001) Gap Statistic

The alternative test statistic to the LR test is the Gap Statistic. The Gap Statistic effectively measures the most probable within sum-of-square distances from a set of Monte Carlo samples which are derived from the original dataset. After the adjustment of a simulation and estimation error, the optimal number of clusters is determined. The estimation of the Gap Statistic can be operationalised by employing the following four step procedure;

Step 1: Cluster the observed data and vary the number of groups from k = 1, 2,..., K, thus generating within-dispersion measures W_K , k = 1, 2, …, K.[10]

Step 2: Generate B reference data sets, using either the uniform distribution or the singular variance decomposition (SVD) method, and then cluster each one giving within-dispersion measures W^*_{kb}, b = 1, 2, …, B, k = 1, 2, …, K. This allows the calculation of the Gap statistic as;

$$Gap_n(k) = E^*_n\{\log(W_k)\} - \log(W_k) \tag{4}$$

where: E^*_n is the expectation under a sample of size n drawn from the reference distribution. Effectively, the Gap Statistic estimates the $\log(W_k)$ and compares it with its expectation under an appropriate null reference distribution of the data. Thus, the Gap Statistic estimate of the optimal number of clusters in the dataset is the value of k for which $\log(W_k)$ falls the farthest below this reference curve.

[10] The innovative feature of the Gap Statistic is its capacity to accurately estimate the optimal number of clusters in a dataset ranging from *1* to *N* clusters. The earlier test statistics developed by Calinski and Harabasz (1974), Krzanowski and Lai (1988), and Kaufman and Rousseeuw (1990) could only detect the optimal number of clusters ranging from *2* to *N* groups and were not able to test the possibility of a one or single cluster solution. The Gap Statistic mathematically compares the within-cluster sum of squares distance of a given clustering with an average obtained from a set of trials of randomly selected data from the original dataset. The initial procedure is to let the dataset $\{x_{ij}\}$ consist of n observations and p features or characteristics, where i = 1, 2, ..., n, and j = 1, 2,..., p. Second, the squared Euclidean distance estimated in the Gap Statistic differs from a standard clustering procedure. The Euclidean distance in a standard k-means cluster analysis measures the distances of each observation to its cluster mean. In contrast, the Euclidean distance in the Gap Statistic measures the distance between each observation. Each observation in a dataset is denoted as i, let the distance between observation i and observation i' equate to $d_{ii'}$. The squared Euclidean distance in the Gap Statistic can therefore be mathematically described as $d_{ii'} = \sum_j (x_{ij} - x_{i'j})^2$. For a dataset grouped into k clusters, $C_r = C_1, C_2, ...C_k$, where C_r denotes the indices of observations in cluster r, and n_r refers to the number of observations in C_r, then the sum of the pairwise distances for all datapoints in cluster r is denoted as $D_r = \sum_{i,i' \in C_r} d_{ii'}$. Thus, the pooled within-cluster sum of squares around the cluster mean for cluster k is mathematically described as $W_k = \sum_{r=1}^{k} \frac{1}{2n_r} D_r$.

Step 3: Let $\bar{l} = (1/B)\sum_{b=1}^{B}\log(W_{kb}^{*})$ (5)

$$sd_k = [(1/B)\sum_{b}\{\log(W_{kb}^{*}) - \bar{l}\}^2]^{1/2} \quad (6)$$

$$s_k = sd_k\sqrt{(1+1/B)}\ . \quad (7)$$

where

$\bar{l}$ = average pooled within-cluster sum of squares from B samples,

sd_k = standard deviation, and

s_k = a form of standard error estimation.

Step 4: The sample datasets are drawn from the reference distribution via Monte Carlo method of randomly generating the datapoints from the original dataset. Due to the expectations E_n^* being randomly generated from the reference distribution, the sampling distribution must be considered. Thus, the estimate $\hat{k}$ (i.e. the optimal estimated number of clusters) will be the value maximising $\text{Gap}_n(k)$ after the adjustment for the sampling distribution in $E_n^*\{\log(W_k)\}$. This means that the optimal estimated number of clusters, $\hat{k}$, can be expressed as;

$$\hat{k} = \text{smallest } k \text{ such that } Gap(k) \geq Gap(k+1) - s_{k+1} \quad (8)$$

This study generated a total of ten reference datasets for each Gap Statistic trial and 1,000 trials for each test to ensure its accuracy.[11]

[11] The trials were limited to 1,000 trials for each test due to the large computational time involved in estimating each single trial.

Gap Statistic Reference Distribution

The Gap Statistic provides two choices of reference distribution, namely, a uniform distribution and a singular value decomposition (SVD) method to derive a set of principal components of the data. The uniform distribution approach draws samples uniformly over the range of funds for each time period and has the advantage that it is straight-forward and simple to employ. The second method of reference distribution for the Gap Statistic is the SVD method, which involves the generation of principal components of the data. This technique transforms the original dataset into a new set of uncorrelated variables referred to as principal components, which are a product of matrices. If X is the n x p data matrix, the SVD method assumes that the columns have a mean of zero and the singular variance decomposition is computed in (9) as;

$$X = UDV^T \tag{9}$$

The data is transformed via $X' = XV$ and then uniform features Z' are drawn over the ranges of the columns of X' as in the simple uniform method. Finally, a back transformation via $Z = Z'V^T$ is performed to give reference data Z.

The SVD method has the advantage of taking into account the shape of the data distribution and makes the procedure rotationally invariant. The advantage derived from a rotationally invariant procedure is that the sample datasets drawn from the SVD reference distribution method are more likely to replicate the distribution of the original dataset. The SVD method highlights the weakness in the simple uniform distribution approach whereby the sample datasets drawn from the uniform distribution may contain datapoints, which are not representative of the original dataset. Although the uniform method inherently has minor limitations, this study will estimate the reference distribution of the Gap Statistic by employing the more thorough SVD method.[12]

[12] Refer to Greene (2000) for an introduction to Singular Variance Decomposition (SVD) in an econometric setting. For a more general treatment of SVD, see Meyer (2001).

Table 2 Data Collection

This table reports the initial number of hedge fund survivors and non-survivors available for analysis from TASS. The details of the exceptions found in the dataset are summarised. Some funds exhibited more than one exception thus overlapping funds reduced the number of funds to be deleted in the non-survivors dataset. This left 3,012 funds available for analysis, which was composed of 1,836 survivors and 1,176 non-survivors. Of the survivors in this dataset, a total of 371 funds contained a full 92 month performance history which covers the entire test period from January 1994 to August 2001.

	TOTAL		SURVIVORS		NON-SURVIVORS	
	Number	%	Number	%	Number	%
Initial No. of Funds	3,130		1,909		1,221	
Funds With Exceptions						
Quarterly Reporting	27	0.86%	11	0.58%	16	1.31%
Undisclosed Currency	15	0.48%	1	0.05%	14	1.15%
Unassigned Style	9	0.29%	0	0.00%	9	0.74%
Gross Return Data	36	1.15%	19	1.00%	17	1.39%
No Return Data	42	1.34%	42	2.20%	0	0.00%
Total No. of Exceptions	129	4.12%	73	3.82%	56	4.59%
Funds with overlaps	11	0.35%	0	0.00%	11	0.90%
Total No. Deleted	118	3.77%	73	3.82%	45	3.69%
No. of Funds for Analysis	3,012	96.23%	1,836	96.18%	1,176	96.31%
Survivors with complete performance history.			371			

4. DATA

The study employed the hedge fund dataset from Tremont TASS Europe Ltd (hereafter referred to as 'TASS') who are an independent global hedge fund database vendor. The dataset consists of both current hedge fund survivors and non-survivors. Hedge fund non-survivors are defined as funds who cease reporting to TASS.[13] This study follows the works of Fung and Hsieh (2000) and Liang (2000) by analysing hedge fund return from January 1994 onwards, as this is the period whereby data vendors such as TASS commenced the archiving of hedge fund non-survivors. The commencement date of January 1994 is employed in order to reduce the contamination of survivorship bias, therefore, this study was conducted on ninety-two monthly observations for the period January 1994 to August 2001.[14] All non-US dollar denominated hedge fund returns were converted to US dollar equivalents using the respective monthly foreign exchange rate at the end of each month sourced from the United States Federal Reserve.

The analysis of the database resulted in the exclusion of 3.67% of the original dataset for the various reasons which are described in Table 1. A total of 3,012 hedge funds were available for analysis, which was composed of 1,836 survivors and 1,176 non-survivors. Of the 1,836 hedge fund survivors, a total of 371 hedge fund survivors contained a complete performance history spanning the entire 92 month sample. This group of 371 funds will hereafter be referred to as the '371 hedge fund survivors'.

The TASS hedge fund database is similar to other fund databases whereby fund performance histories commence and cease in the database at various points in time. This feature in the TASS database reflects the normal life cycle of hedge funds and their reporting cycle as they commence and cease operations at different time periods. In econometric terms, this type of dataset is more commonly referred to as a 'heterogeneous panel', while in the survival analysis literature, this type of dataset is said to contain 'right censored' data[15].

[13] See Liang (2000) and Fung and Hsieh (2000) for comprehensive reviews on why hedge funds cease to report.

[14] Refer to Fung and Hsieh (2000) and Liang (2001) for a review of hedge fund survivorship.

[15] Refer to Elandt-Johnson and Johnson (1980) for a detailed review of right-censored data, which occurs frequently in the survival analysis literature. This type of dataset is common when estimating the survival analysis of a medical operation and data is collected on patients that have commenced

The issue of hedge fund survivors and non-survivors entering and exiting the dataset is not a trivial matter as the feature of missing values in the dataset may cause serious problems and biases when employing various types of mathematical algorithms. At this point in the study, the choice was considered whether to make assumptions regarding constructing hypothetical return data and inserting hypothetical returns into the datapoints with missing values. The choice to create synthetic data for the funds with missing values would have required the modeling of the source and the shape of hedge funds returns to various risk factors and asset classes (such as the S&P500 and/or a bond index). The work of Lo (2001) and Fung and Hsieh (2002b) suggest that the use of standard econometric models to model hedge fund returns may be regarded as dubious and controversial, at best. After careful consideration, it was decided to leave the dataset in its original form and proceed with this study by making no assumptions in regards to the funds that contain missing values. If at all, the introduction of synthetically constructed data into the missing values would itself impose 'survivability' into the data, which therefore would create a new form of bias in the dataset and in the results. The data collection process in this study highlights the empirical issues confronting plan sponsors when they conduct hedge fund research and they face the challenges of data problems, biases and missing values. This study actively confronts these data issues by making no assumptions or modifications to the data.

5. RESULTS

This study addresses the following research questions. First, what is the impact on style analysis when you include survivors and non-survivors? Second, how many hedge fund investment styles are there in long term and are there any short term dynamics? The answers to these research questions on hedge fund style analysis are important to plan sponsors. In order to address these research questions, the analysis divided in the form of two tests.

Test 1 is conducted on the dataset of hedge fund survivors and non-survivors. In order to include non-survivors into the Gap Statistic, the test requires a full performance

treatment at different time periods and then later die at various time periods while other patients may in fact be still alive at the end of the data sample.

history for each fund. To incorporate the full history of non-survivors, the length of the Gap Statistic was limited to three year time horizons so that survivors and non-survivors with a full performance history were included in the test. The limitation of Test 1 is that the Gap Statistic estimate is limited to three year time horizons as the inclusion of non-survivors does not allow the Gap Statistic estimate to be calculated beyond three years time periods. The estimation of the Gap Statistic using the available hedge funds during those specific time periods was considered in light of the issues that a plan sponsor would face when dealing with the realistic problem of missing values due to hedge funds commencing and ceasing their performance history at various time intervals.

Test 2 is performed on the dataset consisting of the 371 hedge fund survivors who have a full performance history for the period 1994-2001. The rationale for Test 2 is to estimate the number of hedge fund styles using the Gap Statistic over the long term. The limitation of Test 2 is the exclusion of hedge fund non-survivors in the estimation. The long term Gap Statistic estimate of three hedge fund styles over the long term is cross tabulated back to the original TASS categories so that the information content of the results can be more carefully considered. The TASS classification system groups the hedge fund dataset into the eleven broad categories of: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Managed Futures, Fund of Funds and Other.[16]

[16] Refer to the CSFB/Tremont TASS Database and www.tassresarch.com for a detailed description of the various TASS database hedge fund investment styles.

Table 3 Descriptive Statistics of Hedge Fund Survivors and Non-Survivors

The descriptive statistics of 3,012 hedge funds which are comprised of 1,836 survivors and 1,176 non-survivors for the period January 1994 to August 2001. The statistics are based on monthly return data.

Categories	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque Bera
All Funds (inc FOFs)	0.99%	925.14%	-94.03%	6.91%	17.99	2221.66	29143485850**
All Funds (ex FOFs)	1.07%	925.14%	-94.03%	7.40%	18.03	2080.34	20762365316**
Convertible Arbitrage	1.06%	38.73%	-38.05%	2.98%	-0.827	25.85	132211**
Dedicated Short Bias	0.42%	66.01%	-56.76%	8.34%	0.097	11.33	3731**
Emerging Markets	0.63%	137.45%	-85.49%	9.21%	0.481	19.89	132835**
Equity Market Neutral	1.02%	49.09%	-24.39%	3.47%	0.899	14.27	16491**
Event Driven	1.06%	184.16%	-64.31%	4.04%	5.858	286.25	50738247**
Fixed Income Arbitrage	0.75%	44.25%	-41.14%	3.51%	-1.714	34.75	221848**
Fund of Funds (i.e. FOFs)	0.68%	71.87%	-78.40%	4.20%	0.073	27.41	660961**
Global Macro	0.76%	925.14%	-89.71%	12.57%	55.567	4074.12	4922703924**
Long/Short Equity Hedge	1.51%	122.46%	-78.01%	7.54%	1.013	18.29	419534**
Managed Futures	0.66%	298.12%	-94.03%	7.87%	5.025	182.25	26834262**
Other	0.85%	57.46%	-58.91%	6.14%	-0.775	21.92	25522**

* Significant at 5% level.

** Significant at 1% level.

Table 4 Likelihood Ratio (LR) Test Statistics on Survivors and Non-Survivors

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This table provides the results of the likelihood test statistic on dataset of hedge fund survivors and non-survivors for the period 1994 to 2001. The test statistic shows that the likelihood ratio test statistic shows significant p-values from three to twelve hedge fund investment styles. Note that the p-values are either 0 or 1 due to the large chi-squared statistics. The high degrees of freedom under this test results in a chi-squared statistic with a narrow density function which results in p-values predominantly at the extremes of either 0 or 1.

No. of Styles	1	2	3	4	5	6
χ^2 Statistic	N.A.	N.A.	995,225	549,607	272,099	750,650
P-Value	1	1	1	1	1	1

No. of Styles	7	8	9	10	11	12
χ^2 Statistic	554,648	368,130	315,087	275,153	277,944	275,978
P-Value	1	1	1	1	1	1

Test 1: Dataset of Survivors and Non-Survivors

The first test estimates the Gap Statistic on the dataset which includes both survivors and non-survivors combined for the various three year time horizons. The analysis on this dataset is performed in order to account for any survivorship bias impacts on the results.[17] The descriptive statistics of the hedge fund survivors and non-survivors in Table 3 provide substantial evidence to suggest that hedge fund returns violate the assumptions of IID returns. These results lend support to Lo (2001) and Lochoff (2002) who reported similar characteristics in hedge fund returns. It is clear that hedge fund investment style analysis requires a model where the assumption of normally distributed returns can be relaxed.

Likelihood Ratio (LR) Test

This study proceeds to employ the Brown and Goetzmann (1997, 2003) methodology and the traditional LR test to estimate the optimal number of hedge fund styles. The LR test results on the hedge fund survivors and non-survivors are summarised in Table 4 and they indicate large chi-squared statistics in the range of three to twelve hedge fund investment styles. Due to the very large chi-squared statistics, the *p*-values tend to be either 0 or 1.[18] When the LR test generates a *p*-value close to zero, an increase in the number of hedge fund investment styles is required. However, the results in Table 4 show that the LR test statistic (i.e. the *p*-value equal to one) occurs from three to twelve hedge fund investment styles. The statistics in Table 4 illustrate that the LR test statistic tends to estimate too many investment styles or tends to overestimate the number of investment styles in the dataset.

The ambiguous results in Table 4 can be attributed to the LR test's assumption of a χ^2 distribution with *2Tm* degrees of freedom, which follows the work of Brown and Goetzmann (1997, 2003). The skewness, kurtosis and Jarque-Bera test from the descriptive statistics in Table 3 illustrate that the hedge fund returns in this dataset are not normally distributed. Considering that the hedge fund dataset is composed of

[17] Refer to the works of Edwards and Park (1996), Liang (2000), Fung and Hsieh (2000) and Edwards and Caglayan (2001) for detailed analyses of the variety of hedge fund biases being, survivorship, instant history and multiperiod sampling bias.

[18] The large chi-squared statistics are a function of the large degrees of freedom which produces a narrow density function, which results in p-values at the extremes of either 0 or 1.

returns, which are not normally distributed, it is not surprising that the LR test results in Table 4 generated ambiguous results.

The findings of eight hedge fund investment styles in Brown and Goetzmann (2003) differ to the ambiguous results derived in this study and it can be attributed to a number of factors. First, the dataset employed in both studies was the TASS database, however, Brown and Goetzmann (2003) analyse the period 1989 to 1999 while this study analyses the period 1994 to 2001. The second factor that may explain the difference in the two studies is that Brown and Goetzmann (1997, 2003) may have employed rolling rates of return, similar to Sharpe (1992), while this study analyses monthly returns. Considering the small data and methodological differences between Brown and Goetzmann (2003) and this study, one can conclude that the results from the LR test undertaken on this dataset in Table 4 are too ambiguous to provide any insight to the number of hedge fund investment styles.

Gap Statistic

This study then employs the Gap Statistic using the singular variance decomposition (SVD) method to estimate the number of hedge fund investment styles. In order to evaluate the impact of fund survivorship, the Gap Statistic was employed on the dataset of hedge fund survivors and non-survivors who were alive during each of the various three year time periods.[19] The Gap Statistic results are summarised in Table 5.

[19] As the Gap Statistic calculation can not accept funds with missing return values, this test excludes hedge fund survivors and non-survivors who may have had a partial performance history over the various test periods. While this study attempts to incorporate survivorship effects by including hedge fund non-survivors, a residual level of bias still exists in this study.

Table 5 Gap Statistic on Hedge Fund Survivors and Non-Survivors

This table represents the results of the Gap Statistic based on 1,000 trials on the hedge fund survivor and non-survivors dataset. The Gap Statistic was estimated based on three year time periods with was composed of different hedge fund survivors and non-survivors for each test period. The Gap Statistic calculation was performed from 1 to 12 groups, however, the estimates for 8 to 12 groupings are not reported as they resulted in nil output.

Years	No. of Funds In Sample	Estimated Number of Groups (Investment Styles)						
		1	2	3	4	5	6	7
1994-1996	665	0%	0%	17.3%	82.7%	0%	0%	0%
1995-1997	827	0%	99.5%	0.5%	0%	0%	0%	0%
1996-1998	963	98.1%	1.9%	0%	0%	0%	0%	0%
1997-1999	1,092	0%	7.1%	0%	92.9%	0%	0%	0%
1998-2000	1,204	0%	0%	90.2%	7.8%	0%	0%	0%
1999-2001	1,296	0%	22.4%	0%	77.6%	0%	0%	0%

The Gap Statistic estimates from Table 5 provide insightful information. First, it is clear that the Gap Statistic estimates the presence of one to four hedge fund investment styles depending on the time period. Second, the Gap Statistic results vary for each test period and this can be attributed to the short run effects caused by the small three year time horizon windows and the changing composition of the hedge funds in each test period. The findings in Table 5 differ to Fung and Hsieh (1997) who provide evidence of five or eight hedge fund styles and Brown and Goetzmann (2003) who estimate the presence of eight hedge fund investment styles. The Gap Statistic provides evidence that there are no more than four hedge fund investment styles when three year time horizon tests are performed. The inclusion of non-survivors in this test has a limitation, as the Gap Statistic is restricted to three year time horizons only so that non-survivors with a full three year performance history can be included in the estimate. This study proceeds to consider the Gap Statistic estimate over the long term.

Table 6 Descriptive Statistics of 371 Hedge Fund Survivors

The descriptive statistics of 371 hedge funds who possess the full history of performance returns from 1994 to 2001. The statistics are based on monthly return data.

Categories	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque Bera
All Funds (inc FOFs)	0.95%	74.97%	-88.68%	5.38%	0.195	18.828	356527.93**
All Funds (ex FOFs)	1.02%	74.97%	-88.68%	5.84%	0.216	17.240	217861.57**
Convertible Arbitrage	0.80%	15.49%	-27.73%	3.16%	-2.632	26.489	28875.88**
Dedicated Short Bias	0.25%	66.01%	-56.76%	8.06%	-0.129	17.693	4966.75**
Emerging Markets	0.26%	39.14%	-44.51%	8.69%	-0.033	7.161	1327.67**
Equity Market Neutral	1.11%	21.14%	-11.42%	3.58%	0.731	7.082	504.523**
Event Driven	1.06%	50.50%	-39.12%	3.10%	0.668	45.255	411063.24**
Fixed Income Arbitrage	0.64%	44.25%	-21.09%	3.00%	4.896	91.379	181856.29**
Fund of Funds (i.e. FOFs)	0.73%	29.50%	-46.91%	3.63%	-0.460	15.829	57705.03**
Global Macro	0.87%	37.00%	-19.29%	4.49%	1.601	13.297	6685.948**
Long/Short Equity Hedge	1.37%	49.55%	-53.24%	6.07%	0.430	9.953	19191.145**
Managed Futures	0.80%	74.97%	-88.68%	7.35%	0.110	17.321	39316.742**
Other	0.98%	4.32%	-4.77%	1.46%	-1.058	5.738	45.885**

* Significant at 5% level.

** Significant at 1% level.

Table 7 Likelihood Ratio (LR) Test Statistics on 371 Hedge Fund Survivors

This table provides the results of the likelihood test statistic on dataset of hedge fund survivors and non-survivors for the period 1994 to 2001. The test statistic shows that the likelihood ratio test statistic shows significant p-values from three to twelve hedge fund investment styles. Note that the p-values are either 0 or 1 due to the large chi-squared statistics. The high degrees of freedom under this test results in a chi-squared statistic with a narrow density function which results in p-values predominantly at the extremes of either 0 or 1.

No. of Styles	1	2	3	4	5	6
χ^2 Statistic	N.A.	N.A.	7,097	3,961	3,202	2,006
P-Value	1	1	1	1	1	1

No. of Styles	7	8	9	10	11	12
χ^2 Statistic	5,578	3,383	2,637	2,265	1,884	1,998
P-Value	1	1	1	1	1	1

Test 2: Analysis of the 371 Survivor Dataset

As plan sponsors analyse and consider allocation to hedge funds, it is important to know the number of different hedge fund investment styles that exist over the long term. While the inclusion of non-survivors in Test 1 allows the study to estimate the impact of survivorship, it does not provide a long term Gap Statistic estimate of styles. The first test estimated the Gap Statistic for short term time horizons which provided evidence that the number of hedge fund styles can be statistically estimated at up to four investment styles. In order to generate the Gap Statistic over the long term, this study considers the sample of 371 hedge funds that have the full 1994-2001 performance history. It is clear that the data employed in this second test excludes all non-survivors and any current survivors that do not have a full performance history. In other words, while this study attempts to estimate the Gap Statistic over the long term, it does so by paying the price of introducing a type of survivorship bias into the analysis. The results of Test 2 are the same as Test 1, but with the inclusion of the long term Gap Statistic estimate. The descriptive statistics of the 371 hedge fund survivor dataset are provided in Table 6.

The descriptive statistics in Table 6 are consistent with the previous results in Table 3. The descriptive statistics of the 371 survivors possess skewness, kurtosis and Jarque Bera statistics suggest that the returns are not normally distributed. The evaluation of Table 3 and Table 6 indicate that the non-normality of hedge fund returns are not related to survivorship as both datasets exhibit non-normal distribution of returns.

Likelihood Ratio (LR) Test

The LR test on the 371 hedge fund survivors are provided in Table 7. The LR test on the 371 survivors is consistent with the LR test results on both survivors and non-survivors. Both LR tests exhibit large chi-squared statistics in the range of three to twelve hedge fund investment styles and the very large chi-squared statistics, generates *p*-values which tend to be either 0 or 1. Once again, the LR test generated in this study fails to provide insight to the number of hedge fund investment styles. This study proceeds to estimate the Gap Statistics on the 371 hedge fund survivors.

Table 8 Gap Statistic on the 371 Hedge Fund Survivors

This table represents the results of the Gap Statistic based on 1,000 trials on the 371 hedge fund survivors only. The Gap Statistic was estimated based on three year time periods and for the full 1994-2001 period. The Gap Statistic calculation was performed from 1 to 12 groups, however, the estimates for 8 to 12 groupings are not reported as they resulted in nil output.

Years	No. of Funds In Sample	Estimated Number of Groups (Investment Styles)						
		1	2	3	4	5	6	7
1994-1996	371	0%	0%	98.0%	2.0%	0%	0%	0%
1995-1997	371	0%	0%	92.8%	7.2%	0%	0%	0%
1996-1998	371	0%	17.6%	8.8%	29.7%	44.0%	0%	0%
1997-1999	371	0%	91.5%	0%	8.5%	0%	0%	0%
1998-2000	371	0%	0%	16.2%	83.8%	0%	0%	0%
1999-2001	371	0%	0%	99.6%	0.4%	0%	0%	0%
1994-2001	371	0%	0%	84.0%	0.0%	0%	10.9%	5.1%

Gap Statistic

The results of the Gap Statistic on the 371 hedge fund survivors are provided in Table 8. The Gap Statistic was calculated on the 371 hedge fund survivors over the same three year time horizons as in Test 1, and the results from Test 2 indicate the presence of up to five investment styles over short term three year time periods. The difference in results between Test 1 and Test 2 clearly show the evidence of an upward bias in the estimation of the Gap Statistic when one excludes the impact of non-survivors over the short term three year time horizons.

The Gap Statistic for the entire 1994-2001 period was then calculated to estimate the optimal number of hedge fund investment styles over the long term. The Gap Statistic for the entire period 1994-2001 demonstrates that 84% of the 1,000 Gap Statistic simulations indicate the statistical presence of three hedge fund investment styles on the 371 hedge fund survivors only. These findings are in stark contrast to the work of Fung and Hsieh (1997) who estimates five or eight styles and Brown and Goetzmann (2003) who estimated eight hedge fund styles. It is noteworthy that the Gap Statistic for the full period also finds the presence of six and seven hedge fund investment styles at times, however, these simulations are not statistically significant when compared to the historical presence of three hedge fund investment styles. Considering that the Gap Statistic calculates statistically insignificant estimates of six to seven hedge fund styles, the findings provides evidence that the estimate of eight hedge fund investment styles in Brown and Goetzmann (2003) may indicate the upward biasedness that seems inherent in the LR test.

Table 9 Descriptive Statistics of the Three Gap Statistic Hedge Fund Styles

This table provides the descriptive statistics of the 371 hedge fund survivors when grouped by the three investment styles on the ninety-two month period from January 1994 to August 2001. Panel A sums the number of the 371 hedge fund survivors in each cluster. Panel B is a cross tabulation which shows the TASS category that they were originally assigned to. Panel C contains the descriptive statistics of all data in each cluster and Panel D contains the descriptive statistics of the average monthly returns of each cluster or category. The statistics in this table do not include non-survivors therefore the mean returns in this table must be treated with caution as they contain survivorship bias.
** indicates statistical significance at the 1% level.

	Group 1	Group 2	Group 3	Total
Panel A: Number of Funds In Each Group				
	160	157	54	371
Panel B: Cross Tabulation with TASS Categories				
Global Macro	3	7	5	15
Long/Short Equity Hedge	76	25	1	102
Fund of Funds (FOFs)	41	36	14	91
Event Driven	11	49	0	60
Emerging Markets	17	3	0	20
Managed Futures	9	8	33	50
Equity Market Neutral	1	6	0	7
Convertible Arbitrage	2	11	0	13
Fixed Income Arbitrage	0	6	0	6
Dedicated Short Bias	0	5	1	6
Other	0	1	0	1
Panel C: Descriptive Statistics All Data				
Mean	1.0326%	0.8962%	0.8469%	
Standard Deviation	6.4138%	3.0739%	7.0383%	
Skewness	-0.1491	0.2654	0.8364	
Kurtosis	13.536	29.233	13.511	
Jarque-Bera Statistic	68137.49**	414345.77**	23447.17**	
Panel D: Descriptive Statistics Average Equal Weighted Monthly Datapoints				
Mean	1.0326%	0.8962%	0.8469%	
Standard Deviation	3.7046%	0.7132%	4.0164%	
Skewness	-0.4826	-0.9841	0.5342	
Kurtosis	5.598	6.191	3.291	
Jarque-Bera Statistic	29.45**	53.88**	4.70	

Table 10 Correlation Analysis of the Three Gap Statistic Hedge Fund Styles

This table provides a correlation analysis of the hedge fund returns that are assigned to the three hedge fund styles as estimated by the gap statistic for the period January 1994 to August 2001.

	Group 1	Group 2	Group 3
Panel A: Correlation to the S&P500 All Return Index			
All Months – Correlation	0.461	0.156	-0.055
All Months – 95% Percentile	0.655	0.498	0.148
All Months – 5% Percentile	0.254	-0.331	-0.194
All Months – Maximum	0.943	0.690	0.320
All Months – Minimum	0.155	-0.744	-0.564
Up Months – Correlation	0.233	0.045	-0.020
Up Months – 95% Percentile	0.440	0.317	0.137
Up Months – 5% Percentile	-0.033	-0.234	-0.188
Up Months – Maximum	0.887	0.462	0.248
Up Months – Minimum	-0.179	-0.490	-0.485
Down Months – Correlation	0.389	0.148	-0.128
Down Months – 95% Percentile	0.632	0.501	0.208
Down Months – 5% Percentile	0.074	-0.369	-0.374
Down Months – Maximum	0.844	0.698	0.277
Down Months – Minimum	-0.022	-0.619	-0.479
Panel B: Correlation to Lehman Brothers Bond Index			
All Months – Correlation	0.023	0.031	0.201
All Months – 95% Percentile	0.199	0.210	0.348
All Months – 5% Percentile	-0.125	-0.146	-0.003
All Months – Maximum	0.368	0.587	0.481
All Months – Minimum	-0.235	-0.229	-0.068
Up Months – Correlation	-0.044	0.031	0.195
Up Months – 95% Percentile	0.135	0.210	0.436
Up Months – 5% Percentile	-0.224	-0.146	-0.106
Up Months – Maximum	0.397	0.587	0.540
Up Months – Minimum	-0.389	-0.229	-0.209
Down Months – Correlation	0.196	0.119	0.157
Down Months – 95% Percentile	0.400	0.377	0.333
Down Months – 5% Percentile	-0.051	-0.147	-0.072
Down Months – Maximum	0.510	0.555	0.384
Down Months – Minimum	-0.250	-0.249	-0.155

C. Interpretation of Long Term Gap Statistic Estimate

The findings in this study of three hedge fund styles for the period 1994-2001 is controversial as previous scholars have estimated the presence of five to eight styles while industry practitioners classify hedge funds into many more style categories. These results are of interest to plan sponsors as they are interested in the correlation metrics of these three hedge fund styles in order to employ these hedge fund investment styles in an asset allocation process. Another point of interest in this study is that the 371 hedge fund survivors with full performance histories represent only 12.3% of the entire 3,012 hedge fund sample. What are the long run characteristics of the three hedge fund investment styles estimated by the Gap Statistic on these 371 hedge fund survivors? This study finds that nearly half of the 371 hedge fund survivors have a high correlation to a stockmarket proxy that it can be said that their style is associated with a long equities exposure.

To better understand the long term Gap Statistic estimate of three hedge fund styles from Test 2, the dataset of the 371 hedge fund survivors is cross referenced with the TASS investment style classifications. Table 9 provides the descriptive statistics of the funds in the three hedge fund investment styles, while Table 10 is a correlation analysis which compares the three hedge fund investment styles against a stockmarket and bond proxy. The cross-tabulation results in Table 9 and Table 10 provide information content on how the Gap Statistic has statistically classified the hedge fund industry into the three investment styles. The analysis of the results from Table 9 and Table 10 are summarised in the following three headings which describe the characteristics of the three hedge fund investment styles as determined by the Gap Statistic.

Hedge Fund Investment Style 1- Quasi Long Equity

The first investment style is concentrated with 76 of the 102 long/short equity hedge funds and 41 of the 91 fund of funds in grouped in this category. This investment style category generated a historical mean monthly return of 1.03 per cent with a standard deviation of 6.41 percent. The results in Table 10 suggest that the funds grouped in this style have a strong positive correlation to the S&P500 in all months, up and down months and they have a generally low correlation to the Lehman Bond

Index. Another interesting feature was that 160 funds or 43.1% of the entire 371 survivor sample were classified into this hedge fund investment style.

This quasi-long equity investment style exhibits a positive correlation to the stockmarket proxy, and this is consistent, considering that it contains a large proportion of funds belonging in long/short equity hedge, fund of funds and emerging markets. When one considers the univariate association to equities, this hedge fund style would add little or no benefit for a plan sponsor. These hedge funds tend to exhibit characteristics of a semi-cash, semi-stock type fund or a low beta stockmarket fund. Funds that are grouped in this category would find it difficult to justify high levels of management or incentive fees considering that investors could replicate such as strategy through the use of index funds and cash. It is surprising that such a large proportion of hedge funds in this sample have such a positive correlation to the S&P500 stockmarket index. While industry peer based classifications consider the long/short equity hedge style and fund of funds style as different investments to long only equities, the Gap Statistic estimate has categorised these funds into the same style grouping that tend to behave like long-only equity exposures. Plan sponsors must consider the rationale for investment in hedge funds which behave similarly to stock markets. The findings that long/short equity hedge managers exhibit exposures that proxy a long position in stockmarkets is consistent with similar findings by Asness, Krail and Liew (2001) and Fung and Hsieh (2002a).

Hedge Fund Investment Style 2- Non-Directional

This second investment style contains 49 of 60 event driven funds, 6 of the 7 equity market neutral funds, 11 of the 13 convertible arbitrage funds, all of the 6 fixed income arbitrage funds and 5 of the 6 dedicated short bias funds. This hedge fund style category generated a historical mean monthly return of 0.90% with a standard deviation of 3.07%. This hedge fund category earns approximately 90 per cent of the average monthly returns of Style 1 but with half of the volatility of the Style 1 returns. This low standard deviation feature is consistent with non-directional strategies and this is supported by the fact that a majority of the 371 funds in the non-directional based styles of fixed income arbitrage, convertible arbitrage and equity market neutral have been classified into this hedge fund investment style.

The funds in this investment style, on average, have a relatively low correlation to both stocks and bonds. The correlation characteristics of Style 2 differ markedly to Style 1, which suggests that the sources of returns from Style 2 are not dependant on the direction of traditional asset classes. The "non-directional" nature of Style 2 is supported by the evidence that this category is composed of funds from various asset classes, yet their returns have been classified into the same investment style. This is significant as it implies that the sources of these hedge fund returns are not related to the asset class, but rather, the sources of these returns are related to the non-directional nature of this investment style. These findings are consistent with the previous work of non-directional styles in Lo (2001) and Fung and Hsieh (2002a). The hedge funds classified in investment Style 2 clearly exhibit characteristics that would fulfill the role of hedge funds in an asset allocation process, whereby they generate returns that have a low correlation to traditional asset classes. Hedge funds in this investment style category can partially defend their claim for specialised management fees as they provide plan sponsors with returns which are not correlated to stocks or bonds

Hedge Fund Investment Style 3- Global Directional

Style 3 is dominated by 33 of the 50 managed futures funds. Managed futures are a fund category which is dominated by trend following based strategies and this investment style group exhibits the highest level of volatility in returns. Unlike the previous two hedge fund categories, this investment style exhibits a low correlation to the S&P500 and only a slightly positive correlation to the Lehman Bond Index. In fact, this group of hedge funds, on average, tend to have an inverse correlation to the S&P500 during down months. This finding is consistent with the work of Fung and Hsieh (2002a). This investment style exhibits a unique set of correlation metrics with the S&P500 which does not exist with the other two hedge fund styles. In addition, this category of hedge funds, on average, has the lowest level of kurtosis and the highest level of positive skewness. This indicates that its distribution has a long right tail, which is more favourable than the skewness and kurtosis characteristics of the previous two styles. Hedge funds in this investment style can defend the claim for management fees considering that they provide investors with partial protection against falls in the stockmarket.

6. CONCLUSION

The estimation of the number of hedge fund investment styles using the Gap Statistic is not an easy task when confronted with the challenges of the data issues in hedge funds. The Brown and Goetzmann (1997, 2003) developed a tool which can classify funds without the knowledge or requirement of asset class exposures. This paper contributes to the hedge fund literature by improving the work of Brown and Goetzmann (2003) by estimating the number of hedge fund styles using the Gap Statistic rather than the traditional LR test. This study calculated the number of hedge fund styles over the long term and the Gap Statistic estimated the presence of three hedge fund styles over the 1994-2001 period. The study also found the presence of short term investment style dynamics of up to five styles over three year time horizons. The findings from this study provides an effective investment style analysis framework for plan sponsors. Asset allocators should avoid hedge funds that exhibit long only type exposures, and alternately, seek hedge funds that are non-directional in nature or those with directional styles that possess low or inverse return characteristics to stockmarket proxies.

The one clear conclusion that the Gap Statistic provides from this study is that it contradicts the academic literature and industry based classification methodologies on hedge fund style analysis. The Gap Statistic estimates over both short term and long term time horizons do not support the presence of five to eight styles as in Fung and Hsieh (1997) or eight styles as stated in Brown and Goetzmann (2003). It is even more opposed to the industry based classification of multitudes of investment styles.

The information content from these three hedge fund investment styles informs us that there seems to be a large proportion of hedge funds that tend to be statistically grouped and positively correlated with a traditional stockmarket proxy. These hedge funds could be better described as low-beta stockmarket funds rather than the catch all classification term of ‘hedge funds’. Alternately, there are also two other hedge fund styles that possess low and sometimes inverse correlations to traditional asset classes, and thus, can be potential candidates in an asset allocation process. The findings from this study will allow future research to focus on identifying the risk factors in the hedge fund industry that can best describe the three dominant investment styles that were estimated from this study.

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