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Interfaces with Other Disciplines

Hedge fund performance appraisal using data envelopment analysis

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Abstract

In this paper we apply data envelopment analysis (DEA) to evaluate the performance of hedge fund classifications. The purpose of alternative investment strategies such as hedge funds is to offer absolute returns, so using passive benchmarks to measure their performance could be ineffective. With the increasing number of hedge funds available, institutional investors, pension funds, and high net worth individuals urgently need a trustworthy efficiency appraisal method. DEA can achieve this. An important benefit of the DEA measure is that benchmarks are not required, thereby alleviating the problem of using traditional benchmarks to examine non-normal distribution of hedge fund returns. We suggest that DEA be used as a complimentary technique (or method) for the selection of efficient hedge funds and funds of hedge funds for investors. Using DEA can shed light and further validate hedge fund manager selection with other methodologies.

Keywords: Data envelopment analysis (DEA); Efficiency; Hedge fund; Performance

1. Introduction

Hedge funds have recently gained popularity and acceptance by institutional investors for diversifying traditional stock and bond portfolios. This alternative asset class traditionally has low correlations with stock and bond markets and offers protection in turbulent markets (Amenc et al., in press). Much recent debate has centered on how to measure and evaluate the performance of hedge funds, therefore comparing hedge funds to standard market indices could be erroneous since hedge funds possess different characteristics than traditional stock and bond funds. In the literature we frequently observe hedge fund rankings

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displayed using measures such as the Sharpe ratio, but this could pose problems due to the option-like returns that hedge funds generate (see Fung and Hsieh, 1997).

The importance and key role hedge funds play by using leverage, short selling and other derivatives strategies could have an influencing effect on portfolio management by providing downside protection. Nevertheless, the inclusion of hedge funds in investor portfolios further requires more accurate methodologies to handle the asymmetrical returns they produce. Particularly, since hedge fund manager selection is a precise process for appraising both risk and reward.

Several authors have used multifactor models to examine hedge fund performance (Edwards and Caglayan, 2001; Gregoriou et al., 2002). However, as Brealey and Kaplanis (2001) note, there are problems inherent in using these types of traditional approaches in a world of non-normal returns. For example, because of their dynamic trading strategies, hedge funds do not have stable exposure to market factors over time, thus resulting in low predictive powers of models. Furthermore, hedge funds are known as absolute return vehicles and their aim is to provide superior performance with low volatility in both bull and bear markets as opposed to comparing their relative performance to traditional market indices. It is not unusual that multifactor models based on indices do not work well for the non-normality of hedge fund returns. Due to their non-normal characteristics, it is difficult to find appropriate active benchmarks, and in some cases traditional benchmarks have been used to compare hedge fund returns resulting in low R-squared values (Gregoriou et al., 2002; Edwards and Caglayan, 2001).

The current paper proposes to compare hedge fund performance using an alternative measure known as data envelopment analysis (DEA) (Charnes et al., 1978). We use three well known DEA models; BCC (Banker et al., 1984), cross-efficiency (Sexton et al., 1986) and super-efficiency (Andersen and Petersen, 1993) to obtain insights due to problems encountered when using multifactor models to predict hedge fund returns.

DEA permits us to appraise and rank hedge funds in a risk–return framework without using indices. The power of DEA is in its ability to deal with several inputs and outputs while not demanding a precise relation between input and output variables. The single measure of performance, which takes into account the multiple measurements of inputs and outputs to estimate a fund's efficiency level, is predominantly practical for evaluating hedge funds, since the hedge funds themselves are used as benchmarks.

Having an alternative performance measure like DEA is important because it enables investors to potentially pinpoint the reasons behind a fund's poor performance. For institutional investors considering using hedge funds as downside protection in bear markets, it is critical that a performance measure provide not only a precise appraisal of the fund's performance, but also an idea of the method management uses to control risk with respect to certain criteria (variables such as inputs and outputs). Using DEA can present investors with a useful tool for ranking hedge funds by self appraisal and peer group appraisal.

The rest of the paper is organized as follows. Section 2 presents some background information on the hedge funds. Section 3 discusses the data and the method. Section 4 presents an application to a set of 614 hedge funds within eight fund classifications. Section 5 concludes.

2. Background information

Hedge funds have frequently been referred to as funds providing "absolute returns" given that their objectives are to offer positive returns irrespective of market conditions while not being compared to any benchmarks. It is commonly known that alternative performance evaluation techniques are essential in calculating the risk exposure characteristics of hedge funds.

Performance measurement is an essential tool for investors and has recently become the central issue for understanding the behavior of hedge funds, especially in bear markets. Many investors' insight of hedge fund performance and manager skill is frequently compared to traditional benchmarks such as the S&P 500 and the Morgan Stanley Capital International World index (MSCI World). However, this comparison could be valid more so for mutual funds than for hedge funds.

Research has also indicated the existing tracking error among various hedge fund indices where some indices are equally weighted while others are value weighted and this could affect performance (McCarthy and Spurgin, 1998). An equally weighted index is preferred to a value weighted index because it reproduces diversification intended to track these types of indices.

Hedge funds have different return characteristics than mutual funds and using standard performance measures to evaluate various hedge fund strategies could be misleading (Fung and Hsieh, 2000). Due to their asymmetric returns, the use of risk-adjusted measures such as the traditional Sharpe ratio is considered unsuitable due to the skewed returns of hedge funds and the dynamic trading strategies they use.

It is difficult to identify factors that drive hedge fund returns, unlike what has been shown for mutual funds. Investors and analysts placing too much faith in these multifactor models are therefore at risk of being mislead, by biased alphas (Schneeweis and Spurgin, 1999). However, the underlying question still remains with reference to which benchmarks would be appropriate for each hedge fund strategy, given that multifactor models using indices could no longer be suitable.

Recent studies, such as Edwards and Caglayan (2001) investigate hedge fund alphas using multifactor models, while Liang (2000) examines survivorship bias of hedge funds. Agarwal and Naik (2000) find significant quarterly performance persistence in hedge funds, while Edwards and Caglayan (2001) observe performance persistence for winners and losers. On the other hand, Brown et al. (1999), Peskin et al. (2000), and Ackermann et al. (1999) uncover slight significant performance persistence, relative to traditional asset classes. The way performance is measured could be the consequence of the divergent results, therefore excess returns could display performance persistence when in fact it is inexistent.

Amenc et al. (in press) using multifactor models partially succeed in explaining the predictability of hedge fund returns for six out of nine hedge fund styles but with low R-squared values ranging from 15.7% to 53.4%. Regardless of the ability of existing and frequently used models to explain hedge fund returns, the dynamic trading strategies and skewed returns remain a serious matter in hedge fund performance literature. Further investigation is warranted to examine this problem by using other innovative methods, possibly DEA.

Fung and Hsieh (1997) and Liang (1999) apply Sharpe's factor "style" analysis to hedge funds and find that very little of the variability in hedge fund returns can be attributed to those of financial asset classes—unlike what Sharpe (1992) observes for mutual funds. They attribute the low R-squared values to the dynamic strategies of hedge funds. Despite its frequent use, the main drawback of Sharpe's style analysis assumes that the exposure to the individual styles do not vary through time. LHabitant (2002) also argues that returns based style performs poorly for hedge funds as a result of their various investment strategies, especially since style analysis calls for consistency during the investigation period.

Agarwal and Naik (2000) apply mean–variance analysis to show that portfolios consisting of passive asset classes (passive investment in equities and bonds) mixed with non-directional hedge funds, provide a better risk–return tradeoff than portfolios with passive asset classes only at the expense of increased negative skewness. Agarwal and Naik (2000) define hedge funds whose returns exhibit low correlation with market indices as having "non-directional" strategies, and those with high correlation as having "directional" strategies. Some authors are beginning to apply longitudinal analyses to better describe temporal features of hedge fund performance. Brown et al. (2001) apply survival analysis to estimate the lifetimes of hedge funds and find these are affected by factors such as their size, their performance and their redemption period.

Investors relying strictly on using volatility as a risk measure for hedge funds is not enough due to their non-normal returns, thereby requiring more appropriate measures, such as skewness and kurtosis. Furthermore, traditional Sharpe ratios will usually overestimate and miscalculate hedge fund performance, given that negative skewness and excess kurtosis are not considered by this risk-adjusted measure (Brooks and Kat, 2001). [2]

Using hedge fund indices to examine performance persistence could also be a drawback, since they are rebalanced and cannot properly reproduce the same composition during an entire examination period, consequently persistence could be wrongly estimated. DEA allows us to bypass the use of troublesome benchmarks.

3. Data and method

We received hedge fund data from Burlington Hall Asset Management made available by Zurich Capital Markets (ZCM) database. We examine eight hedge fund classifications during the 1997–2001 and 1999–2001 periods. The reason we decide to use two periods is to observe if the extreme market event of August 1998 had any impact on various classifications. The short sellers and the long only classifications were eliminated since they only contained a handful of funds and are deemed not sufficient for the analysis. The database provider advised us that using a longer time frame, for example, a 7- or 10-year examination period would have resulted in significantly less funds. Our data set consists of monthly net returns, whereby both management and performance fees have already been subtracted by the hedge funds and forwarded to ZCM. We do not examine defunct hedge funds.

Modern portfolio theory measures the total risk of a portfolio by using the variance of the returns. But this method does not separate the upside risk, which investors seek, from the downside risk they want to avoid. Variance is not typically a good method for measuring risk, but semi-variance is frequently used and accepted in the investment area to measure downside risk. Returns above the mean can hardly be regarded as risky by investors, but the variance below the mean provides more information during extreme market events which confirms that investors worry more about underperformance than overperformance (Markowitz, 1991). [3]

Furthermore, the mean and standard deviations of hedge fund returns could be misleading and higher moments such as skewness and kurtosis will provide a more accurate picture (Fung and Hsieh, 1997). The introduction of skewness in the inputs and outputs will present some signaling assessment of each hedge fund classification. To correctly assess hedge fund appraisal, skewness does not penalize hedge funds by the upside potential returns. Although hedge funds attempt to maximize returns and minimize risk, this comes at a tradeoff, whereby, adding hedge funds to traditional investment portfolios will likely result in high kurtosis and increased negative skewness which are the drawbacks of this alternative asset class. Moreover, hedge funds have fat tails resulting in a greater number of extreme events than one would normally anticipate (Fung and Hsieh, 2000).

The inputs and outputs must correspond to the activities of hedge funds for the analysis to make sense. We use six variables in a risk–return framework, three for inputs and three for outputs, since a larger number might clutter the analysis.

The inputs are: (1) lower mean monthly semi-skewness, (2) lower mean monthly semi-variance, and (3) mean monthly lower return. The outputs are: (1) upper mean monthly semi-skewness, (2) upper mean

[2] Non-normality implies that traditional mean–variance analysis cannot be optimal in this case. The Capital Asset Pricing Model (CAPM) therefore is incorrect because the variance and return do not follow accepted theoretical foundations. As investments, hedge funds display that their low variance provides greater returns and their high variance provides lower returns than what the CAPM presumes.

[3] Extreme market events include the following: the Asian currency crisis of 1997, the Russian ruble crisis of 1998, and the September 11, 2001 terrorist attacks. However, the Russian ruble crisis was considered as the "major" or "most severe" extreme market event, which had the greatest impact on hedge funds. The other two events had little or no impact on hedge funds.

monthly semi-variance, and (3) mean monthly upper return. The value of outputs is the value-added of each hedge fund and the 30-day US T-bill rate is subtracted from the monthly net returns. [4] These measures are chosen because higher output values and smaller input values usually indicate better fund performance.

The data were aggregated into separate DEA runs for the 3-year (1999–2001) and 5-year (1997–2001) periods for each classification. Both examination periods contain the same funds in each classification enabling us to see whether the rankings would differ and if several funds would be efficient in both periods.

Since hedge funds vary their leverage at different times to magnify returns, we employ the BCC model (variable returns to scale) to identify the efficient and inefficient funds. We then use the cross-efficiency and super-efficiency models to further analyze the hedge funds. See Zhu (2002) for a complete discussion of these DEA models.

We have n hedge funds with s outputs, denoted by y_{rk} $(r = 1, \ldots, s)$, and m inputs denoted by x_{ik} $(i = 1, \ldots, m)$, the efficiency measure for fund k is

$$h_k = \mathrm{Max} \frac{\sum_{r=1}^{s} u_r y_{rk} + u_0}{\sum_{i=1}^{m} v_i x_{ik}},$$

where the weights u_r and v_i are non-negative. An additional set of constraints requires that the same weights, when applied to all funds, does not allow any hedge fund with an efficiency score greater than one and is displayed in the following set of constraints:

$$\frac{\sum_{r=1}^{s} u_r y_{rj} + u_0}{\sum_{i=1}^{m} v_i x_{ij}} \leqslant 1 \quad \text{for } j = 1, \ldots, n.$$

The equivalent DEA model can be expressed as

$$h_k = \mathrm{Max} \sum_{r=1}^{s} u_r y_{rk} + u_0$$

subject to

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} + u_0 \geqslant 0 \quad \text{for } j = 1, \ldots, n,$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1,$$

$$u_r \geqslant 0 \quad \text{for } r = 1, \ldots, s,$$

$$v_i \geqslant 0 \quad \text{for } i = 1, \ldots, m.$$

The cross-efficiency model was first seen in Sexton et al. (1986) and later in Doyle and Green (1994) and Anderson et al. (1998, 2002). It establishes the ranking procedure and computes the efficiency score of each hedge fund n times using optimal weights obtained using DEA models. A cross-evaluation matrix consists of rows and columns $(j\ x\ k)$, each equal to the number of hedge funds in the analysis. The efficiency of fund j is computed with the optimal weights for fund k. The higher the values in column k, the more likely that

[4] DEA has been used to evaluate the performance of mutual funds (see McMullen and Strong, 1997; Basso and Funari, 2001; Morey and Morey, 1999; Wilkens and Zhu, 2001). Since hedge funds exhibit non-normal distribution of returns and display fat tails (leptokurtotic), we use different variables than those used for mutual funds.

fund k is an efficient fund using superior operating techniques. Therefore, by calculating the mean of each column will provide the peer appraisal score of each hedge fund. In other words, the peer score is calculated for each fund but the cross-efficiency score is the average of all of a hedge fund's peer scores.

The cross-evaluation model used here is represented by

$$h_{kj} = \frac{\sum_{r=1}^{s} u_{rk} y_{rj}}{\sum_{i=1}^{m} v_{ik} x_{ij}}, \quad k = 1, \ldots, n, \ \ j = 1, \ldots, n,$$

where h_{kj} is the score of hedge fund j cross-evaluated by the weight of hedge fund k. In the cross-evaluation matrix, all funds are bounded by $0 \leqslant h_{kj} \leqslant 1$, and the funds in the diagonal, $h_{kk,}$ depict the DEA efficiency score, $h_{kk} = 1$ for efficient funds and $h_{kk} < 1$ for inefficient funds. The equations show that the problem is generated n times in trying to distinguish the relative efficiency scores of all hedge funds.

Super-efficiency (Andersen and Petersen, 1993) is used to rank the hedge funds. Super-efficiency is obtained from the regular DEA model by excluding the fund under evaluation from the reference set. Because of the infeasibility (Seiford and Zhu, 1999), we use the CCR super efficiency model as follows:

$$h_k = \text{Max} \sum_{r=1}^{s} u_r y_{rk}$$

subject to

$$\begin{aligned}
&\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geqslant 0 \quad \text{for } j = 1, \ldots, n, \ \ j \neq k, \\
&\sum_{i=1}^{m} v_i x_{ik} = 1, \\
&u_r \geqslant \varepsilon \quad \text{for } r = 1, \ldots, s, \\
&v_i \geqslant \varepsilon \quad \text{for } i = 1, \ldots, m.
\end{aligned}$$

We also compare the DEA results with the Sharpe ratio. For risk-adjusted performance, the traditional Sharpe ratio is not applicable for non-normal returns, thus we use instead the modified Sharpe ratio for the comparison of rankings, where we assume the 30-day US T-bill rate for both Sharpe ratios.

$$\text{modified Sharpe ratio} = \frac{R_{\text{pt}} - \text{RFR}}{W\left[\mu - \left\{z_{\text{c}} + \frac{1}{6}(z_{\text{c}}^2 - 1)S + \frac{1}{24}(z_{\text{c}}^3 - 3z_{\text{c}})K - \frac{1}{36}(2z_{\text{c}}^3 - 5z_{\text{c}})S^2\right\}\sigma\right]},$$

where R_{pt} = return of the portfolio, RFR = risk-free rate (30-day US T-bill rate), Z_{c} = is the critical value for probability $(1 - \alpha) - 1.96$ for a 95% probability, S = skewness, K = excess kurtosis.

Additionally, the normal value-at-risk (VaR) is compared to the modified VaR for all classifications and both periods. The comparison will provide us with a more precise picture because the modified VaR takes into account skewness and kurtosis, whereas normal VaR considers only the mean and standard deviation. The modified VaR allows the calculation of VaR for distributions with either positive or negative skewness as well as positive excess kurtosis (or more commonly known as fat tails). We do not discuss the derivation of the modified VaR and the reader is directed to Favre and Galeano (2002).

The normal VaR is represented the following equation and is valid for normal distributions:

$$\text{VaR} = W[\mu\,\mathrm{d}t - n\sigma(\mathrm{d}t)^{0.5}],$$

where W = portfolio, σ = standard deviation, n = number of standard deviation at $(1 - \alpha)$, $\mathrm{d}t$ = time window.

The modified VaR equation is the following:

$$z_{CF} = z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2,$$

where $Z_c =$ is the critical value for probability $(1-\alpha) - 1.96$ for a 95% probability, $S =$ skewness and $K =$ excess kurtosis.

Furthermore, we use the Jarque–Bera statistic test of non-normality which considers both skewness and excess kurtosis to determine whether all classifications in both examination periods exhibit non-normal distribution of returns. The Jarque–Bera statistic is particularly useful for a large number of monthly returns but not practical for small samples. A Jarque–Bera result greater than 6 indicates the distribution is non-normal:

$$\mathrm{JB} = \frac{n}{6}\left[S^2 + \frac{(k-3)^2}{4}\right],$$

where $n =$ number is the sample size, $S =$ skewness, $K =$ excess kurtosis.

We then evaluate the rankings of the three DEA models against the 3- and 5-year modified Sharpe ratio and against compounded return using Spearman's rho correlation ranking test. Finally, we validate and compare the rankings between DEA models to determine whether the comparisons are stable and significantly correlated despite the non-normality of hedge fund returns.

4. Empirical results

Table 1 displays the number of efficiency and non-efficient funds for both examination periods of 1997–2001 and 1999–2001. The results indicate that a greater majority of funds are non-efficient in a risk–return

Table 1
Number of efficient and non-efficient hedge funds 1997–2001 and 1999–2001

Classification	Efficient	Non-efficient	Total
1997–2001			
Funds of hedge funds	10 (6%)	158 (94%)	168
Sector	9 (27%)	24 (73%)	33
Global macro	7 (29%)	17 (71%)	24
Global emerging	6 (20%)	24 (80%)	30
Global established	9 (7%)	124 (93%)	133
Event driven	20 (27%)	53 (73%)	73
Global international	5 (22%)	18 (78%)	23
Market neutral	5 (4%)	125 (96%)	130
Total	71 (12%)	543 (88%)	614
1999–2001			
Funds of hedge funds	20 (12%)	148 (88%)	168
Sector	11 (33%)	22 (67%)	33
Global macro	8 (33%)	16 (67%)	24
Global emerging	12 (40%)	18 (60%)	30
Global established	18 (14%)	115 (86%)	133
Event driven	21 (29%)	52 (71%)	73
Global international	8 (35%)	15 (65%)	23
Market neutral	9 (7%)	121 (93%)	130
Total	107 (17%)	507 (83%)	614

framework according to the inputs and outputs we use. The reason can possibly be attributed to the various extreme market events such as the Asian currency crisis of October 1997 and the Russian ruble crisis of August 1998 yielding increased volatility in global stock and bond markets.

Table 2 displays descriptive statistics for each hedge fund classification. We find that all efficient funds in the 1997–2001 period, except global emerging, display positive skewness, whereas a majority of the non-efficient funds in the 1997–2001 period exhibit negative skewness, lower standard deviation as well as lower mean monthly returns as opposed to efficient funds. The reasons could be that in the non-efficient category the global macro and the sector classifications has no extreme positive or negative returns, on average, during the 1997–2001 period. This can either be attributed to the use of strategies without leverage, or the use of convex strategies (i.e., for example, buying index options) and also hedge of downside risk (i.e., buying options). In other words, hedge funds can be convex on the upside by being protected on the downside (call payoff) and they pay premium by selling the upside (near-at-the-money) and buying options on the extreme negative to reduce volatility and obtain positive skewness. The effect is due to the extreme market event of August 1998 which caused negative skewness for a large majority of non-efficient funds. To properly assess the performance of hedge funds, the length of the examination period is not important, but rather the time series of each hedge fund classification must be long enough to include at least one major extreme negative market event, as is the case during the 1997–2001 period.

In Table 2 the normal Sharpe ratio is higher than the modified Sharpe ratio because the modified frontier computed in a mean modified VaR is often shifted slightly downwards and to the right of the normal frontier (if skewness is negative and excess kurtosis is positive). The modified Sharpe is sensitive to the modified VaR, because if the modified VaR is around 0%, the modified Sharpe will be high.

Investors prefer to reduce the extreme negative events and favor positive as opposed to negative skewness (implying the left tail is fatter than the right tail), since the underlying motivation for hedge funds is their ability to obtain positive returns in flat or down markets. Furthermore, hedge funds advertise (sell) extreme risk which gives negative skewness and positive kurtosis which can be compared to a short put option (Agarwal and Naik, 2000). Adding hedge funds to a traditional stock and bond portfolio to obtain higher risk-adjusted returns and lower volatility will result in a tradeoff between negative skewness and diversification of the portfolio.

Hedge fund returns do not follow normal distributions because their returns are asymmetrical and display fat tails, a finding validated in both Tables 2 and 3, whereby the non-directional strategies [5] display fatter tails (excess kurtosis) than the directional strategies. As well, the non-directional strategies possess lower volatility than directional ones, a fact that is widely known.

The results in Table 2 indicate somewhat high excess kurtosis (fat tails) and low standard deviation in the non-directional strategies (event driven and market neutral). More frequently excess kurtosis is calculated as kurtosis minus 3 to simplify the explanation. A normal distribution has a kurtosis of 3 and an excess kurtosis of zero implies a normal distribution. Whereas, an excess kurtosis greater than zero signifies a high probability of big gains or losses. The greater the positive excess kurtosis the more the distribution will be peaked or leptokurtic. This implies that there are more returns close to the mean with more frequent large positive or large negative returns than a normal distribution of returns. This signifies that there is a high probability that extreme market events will occur, making this distribution spiked when compared to the normal distribution. The possible reason for this occurrence is that the non-directional classification possesses payoffs like short option strategies whereas, the other directional strategies possess long only option strategies. Therefore, hedge funds usually possess positive excess kurtosis (fat tails) than traditional normal distributions. A fat tailed distribution will generally have a greater number of recurrent extreme (larger or

[5] The non-directional strategies include market neutral and event driven funds, whereas the directional strategies include the rest (except for the funds of hedge funds classification, which is a basket of various directional and non-directional strategies).

Table 2
Monthly statistics of efficient and non-efficient funds 1997–2001

Classification	Mean (%)	Minimum one period return (%)	Maximum one period return (%)	Standard deviation (%)	Skewness	Excess kurtosis	Modified VaR 95% (%)	Normal VaR (%)	Modified Sharpe ratio	Sharpe ratio	Jarque–Bera
Efficient hedge funds											
Funds of hedge funds	1.53	−48.98	48.67	4.22	1.14	6.15	−6.53	−8.28	1.93	2.09	436.98
Event driven	1.26	−54.29	88.47	5.42	0.65	3.37	−10.87	−11.34	0.94	1.26	60.64
Market neutral	2.17	−17.20	72.25	5.47	1.92	9.73	1.33	−10.55	0.90	4.95	484.83
Global macro	1.76	−30.01	46.75	6.33	1.02	3.51	−10.44	−12.97	0.40	0.96	115.16
Global international	0.82	−46.19	33.75	7.66	0.49	1.34	−15.01	−17.00	0.22	0.42	22.32
Global emerging	2.76	−63.79	61.78	14.48	−0.27	2.69	−39.40	−30.92	0.18	0.71	36.57
Global established	2.08	−58.59	85.80	7.78	1.12	4.76	−11.62	−16.03	0.44	1.21	158.03
Sector	2.18	−38.35	62.15	7.79	0.31	2.82	−12.90	−15.94	1.12	1.16	106.31
Non-efficient hedge funds											
Funds of hedge funds	0.93	−28.00	21.21	2.86	−0.40	4.49	−7.09	−5.73	0.60	0.86	124.06
Event driven	0.91	−41.65	49.40	4.27	−0.47	4.70	−11.05	−9.02	0.45	0.88	179.24
Market neutral	1.10	−48.73	97.61	3.09	−0.49	5.61	−6.33	−6.08	0.63	1.18	341.98
Global macro	0.99	−53.24	25.73	4.94	0.07	1.95	−10.50	−11.65	0.16	0.28	27.15
Global international	0.78	−44.51	29.51	5.97	−0.42	2.17	−16.53	−13.10	0.11	0.13	38.62
Global emerging	0.81	−73.25	56.11	8.49	−0.61	4.40	−25.47	−18.94	0.06	0.08	162.82
Global established	1.29	−48.38	47.00	5.91	−0.02	2.27	−13.79	−12.46	0.25	0.63	37.75
Sector	1.50	−31.63	42.49	7.40	0.20	2.60	−15.71	−15.81	0.17	0.55	92.36

Table 3
Monthly statistics of efficient and non-efficient funds 1999–2001

Classification	Mean (%)	Minimum one period return (%)	Maximum one period return (%)	Standard deviation (%)	Skewness	Excess kurtosis	Modified VaR 95% (%)	Normal VaR (%)	Modified Sharpe ratio	Sharpe ratio	Jarque–Bera
Efficient hedge funds											
Funds of hedge funds	1.48	−21.30	48.67	3.29	0.85	2.75	−3.35	−6.17	2.02	2.19	70.18
Event driven	1.17	−54.29	88.47	5.61	1.10	3.36	−8.01	−11.87	1.02	1.21	47.54
Market neutral	2.16	−15.92	72.25	4.29	1.45	5.36	3.00	−7.81	2.13	4.17	124.06
Global macro	1.52	−30.01	44.98	6.50	1.10	3.68	−9.97	−13.59	0.25	0.86	60.21
Global international	1.55	−46.19	33.75	7.80	0.70	1.15	−13.29	−16.59	0.28	0.42	10.91
Global emerging	4.36	−27.64	61.78	12.10	0.93	1.74	−16.63	−23.79	0.55	1.11	14.32
Global established	1.81	−58.59	85.80	7.77	0.98	2.59	−11.32	−16.26	0.94	1.13	33.79
Sector	2.35	−38.35	62.15	7.66	0.64	1.29	−10.36	−15.47	0.47	1.19	19.94
Non-efficient hedge funds											
Funds of hedge funds	1.01	−22.87	20.20	2.60	0.57	1.74	−3.98	−5.05	1.15	1.22	15.66
Event driven	0.92	−41.65	49.40	3.68	0.14	1.38	−6.93	−7.65	1.10	1.28	10.14
Market neutral	1.10	−44.84	97.61	2.58	0.16	2.46	−4.54	−5.53	1.18	1.42	41.21
Global macro	0.86	−53.24	61.32	0.45	0.27	1.07	−9.20	−9.51	0.22	0.30	6.78
Global international	0.94	−30.77	60.15	5.58	0.06	0.50	−12.05	−12.14	0.18	0.30	3.15
Global emerging	1.87	−31.76	56.11	7.35	0.36	0.89	−13.17	−15.22	0.34	0.77	0.27
Global established	1.03	−48.38	87.12	5.91	0.36	1.47	−11.22	−12.72	0.22	0.43	0.08
Sector	1.15	−38.37	66.51	7.25	0.46	1.01	−13.12	−15.73	0.16	0.36	8.72

smaller) observations than a typical normal distribution, a finding displayed in the non-directional and funds of hedge funds classifications where volatility is commonly known to be the lowest. The non-directional strategies attempt to take advantage of irregularities in stock and bond markets and perform well during stable market conditions.

However, the non-efficient global macro classification in Table 2 displays positive skewness during the 1997–2001 period, because this style requires movement of global markets to profit from major trends and destabilizing market conditions. When negative skewness is present in the data, it implies that the payoffs of hedge funds are exposed to on the downside more than normally distributed funds. The number of funds with negative skewness is not necessarily good or bad, it merely implies that investors familiar with risk management will be aware of a decrease in expected return will eventually occur to bear this negative skewness.

Furthermore, we notice for directional funds (or sometimes called market timing funds, for example, global macro, global international, global emerging, global established and sector) we observe a high standard deviation with low excess kurtosis, given that they have a greater exposure to market risk than non-directional funds.

Since hedge funds use dynamic strategies and produce non-linear payoffs, we find that in Table 2 the modified VaR is the highest for the market neutral classification. A high modified VaR implies the modified VaR is near to zero, therefore, a high modified Sharpe ratio is due to a modified VaR near zero. As we approach a modified VaR of zero, the modified Sharpe increases exponentially. In other words, modified VaR penalizes funds with extreme negative returns as the modified VaR accounts for negative skewness, and positive excess kurtosis disliked by investors. The modified VaR measures the risk of losing −5% or more 1% of the time, therefore the higher the number (closer to 0%), the better. On the other hand, the global emerging classification has the worst modified VaR during the 1997–2001 period. The difference between the normal and modified VaR comes from the asymmetries in the hedge fund returns distribution (skewness) and from the positive or negative extreme returns (kurtosis). By comparing both normal and modified VaR will illustrate the impact of neglecting extreme market returns of the measure used in a normal VaR. Non-normal distributions are due to negative skewness (concave payoffs due to premium selling) and/or to excess kurtosis due to extreme market events (liquidity/event risk).

When we examine the Jarque–Bera statistic during both examination periods, we observe that Table 2 specifies that during the 1997–2001 period all distributions are non-normal with a greater amount of non-normality for market neutral classification as a result of the extreme market event of August 1998. However, during the 1999–2001 period, extreme market events were inexistent thereby producing a lower degree of non-normality with all classifications. Furthermore, of the non-efficient hedge funds during the 1999–2001 period displayed in Table 3, three directional classifications (global international, global emerging and global established) have normal distributions due to the lack of a "major" extreme market event during the 1999–2001 period.

We also notice that in both Tables 2 and 3 the standard deviations are higher for the efficient funds in both periods, but using a one-tailed *t*-test the *p*-value is only significant for the 1999–2001 period ($p = 0.040$). Because we suspected a priori that efficient funds would have higher mean monthly returns and higher skewness when compared to non-efficient funds, we use a one-tailed *t*-test. The results indicate that mean monthly returns and skewness for efficient funds are higher than non-efficient funds during both the 1997–2001 and the 1999–2001 periods at the 1% level with *p*-values of $p = 0.004$ and $p = 0.013$ respectively for returns and $p = 0.0005$ and $p < 0.0001$ respectively for skewness.

In Table 3 we discover that all efficient and non-efficient funds exhibit positive skewness and can be explained by the lack of severe extreme market events during the 1999–2001 period. The sole directional classification (non-efficient global macro) benefited from positive skewness during this period is owing to its strategy that is based on global economic indicators, as well as to political and macroeconomic views of different countries. Therefore, the global macro classification during the 1999–2001 period could in fact, have had little exposure to market events as indicated by the lower modified VaR when compared to the 1997–2001 period. As well, after August 1998 a great many global macro hedge funds closed due to their use of excess leverage.

Furthermore, the Basle Committee on Banking Supervision and the Sound practices for Hedge Fund Managers report both have managed to impose on the remaining global macro hedge funds in operation more preventative steps in terms of using excess leverage. Recently, Gregoriou et al. (2002) observed that the global macro classification experienced the second lowest median survival time of 3.59 years during the 1990–2001 period.

Tables 4 and 5 compare the rankings of each hedge fund classification using the three DEA models against the modified and traditional Sharpe ratio respectively by means of the Spearman rank correlation coefficient. We find that a great many classifications have weak correlations, but in fact are significantly different from zero. At the same time we also discover low Spearman correlations, however, a great majority of them are significantly different from zero at the 5% and 1% levels. The event driven and global international classifications have the greatest number of non-significant correlations not significantly different from zero at both 5% and 1% levels.

We believe that the rankings of the various DEA models are related to the modified Sharpe ratio therefore, the correlations highlight a positive and significant relationship between the two, though this relation is often weak and could be attributed to outliers in the data. Although we find some small variation of the rankings when compared to the modified Sharpe ratio, it is not possible to conclude that the DEA models have a "decisive" impact on the outcomes of rank ordering.

We find no significant negative correlations, supporting the claim that the observed relationship between the DEA rankings and the modified Sharpe ratio is not due to chance. If it were, we would expect half the significant correlations to be positive and half to be negative. Our robust results validate the precision of the various models used.

In Table 5 we observe that the traditional Sharpe ratio has a tendency to overstate risk-adjusted returns whereas, the modified Sharpe ratio accounts for the extreme market returns making the results more

Table 4
Spearman R correlation analysis rankings of BCC, cross- and super-efficiency vs. modified Sharpe ratio of all hedge funds

Classification	BCC efficiency vs. modified Sharpe ratio		Cross-efficiency vs. modified Sharpe ratio		Super-efficiency vs. modified Sharpe ratio	
	1997–2001	1999–2001	1997–2001	1999–2001	1997–2001	1999–2001
Funds of hedge funds	0.245**	0.247**	0.332**	0.418**	0.243**	0.254**
	(0.001)	(0.001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Sector	0.404**	0.645**	0.412**	0.724**	0.380*	0.601**
	(0.010)	(<0.0001)	(0.009)	(<0.0001)	(0.014)	(<0.0001)
Global macro	0.489**	0.565**	0.520**	0.539**	0.466*	0.629**
	(0.008)	(0.002)	(0.005)	(0.003)	(0.011)	(<0.0001)
Global emerging	0.821**	0.259	0.820**	−0.122	0.822**	0.407*
	(<0.0001)	(0.084)	(<0.0001)	(0.260)	(<0.0001)	(0.013)
Global established	0.537**	0.478**	0.526**	0.359**	0.537**	0.481**
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Event driven	0.172	0.090	0.404**	0.416**	0.172	0.064
	(0.073)	(0.224)	(<0.0001)	(<0.0001)	(0.073)	(0.295)
Global international	0.183	0.403*	0.248	0.500**	0.190	0.234
	(0.201)	(0.028)	(0.127)	(0.008)	(0.193)	(0.141)
Market neutral	0.074	−0.147*	0.227**	−0.092	0.072	−0.184*
	(0.203)	(0.047)	(0.005)	(0.148)	(0.207)	(0.018)

* Significant at the 0.05 level (one-tailed).
** Significant at the 0.01 level (one-tailed).

Table 5
Spearman *R* correlation analysis of rankings of BCC, cross- and super-efficiency vs. Sharpe ratio of all hedge funds

Classification	BCC efficiency vs. Sharpe ratio		Cross-efficiency vs. Sharpe ratio		Super-efficiency vs. Sharpe ratio	
	1997–2001	1999–2001	1997–2001	1999–2001	1997–2001	1999–2001
Funds of hedge funds	0.366**	0.505**	0.427**	0.560**	0.367**	0.501**
	(<0.0001)	(<0.0001)	(<.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Sector	0.530**	0.764**	0.435**	0.736**	0.521**	0.721**
	(0.001)	(<0.0001)	(0.006)	(<0.0001)	(0.001)	(<0.0001)
Global macro	0.762**	0.513**	0.867**	0.729**	0.744**	0.500**
	(<0.0001)	(0.005)	(<0.0001)	(<0.0001)	(<0.0001)	(0.006)
Global emerging	0.836**	0.224	0.838**	−0.108	0.838**	0.391*
	(<0.0001)	*(0.084)*	(<0.0001)	(0.285)	(<0.0001)	(0.016)
Global established	0.536**	0.547**	0.543**	0.432**	0.535**	0.548**
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Event driven	0.172	0.053	0.308**	0.397**	0.163	0.045
	(0.072)	(0.327)	(0.004)	(<0.0001)	(0.084)	(0.351)
Global international	0.306	0.343	0.540**	0.544**	0.299	−0.036
	(0.078)	(0.055)	(0.004)	(0.004)	(0.083)	(0.466)
Market neutral	0.336**	0.149*	0.439**	0.099	0.337**	0.180*
	(<0.0001)	(0.046)	(<0.0001)	(0.130)	(<0.0001)	(0.020)

* Significant at the 0.05 level (one-tailed).
** Significant at the 0.01 level (one-tailed).

correct. If we accept the traditional Sharpe ratio to measure hedge fund performance, then the results are likely to increase returns and reduce variances and correlations.

Table 6 displays the rankings among the three DEA models to verify the consistency of the models. The results are overwhelming and all models indicate very high Spearman correlation in all classifications and are all significant at both the 5% and 1% levels. We observe that the coefficients reveal that the BCC, cross- and super-efficiency models are consistent in ranking the efficiency of hedge funds.

In Table 7 we find a similar pattern as Table 4, however, the correlations are significantly stronger especially for the market neutral and the funds of hedge funds classifications. The explanation lies in the low volatility and low exposure of these two classifications to market risk. Again, we find no evidence of negative correlations but we do witness weak correlations once more in the event driven and the global international classifications. We conclude there is a strong relation between compounded return and the DEA models.

In Table 8 we notice strong Spearman correlations except for non-directional classifications (market neutral and event driven) although they are significantly different from zero at the 1% level. Due to the low and stable returns of both these classifications, it is common knowledge they are more common in investment portfolios than directional funds. From these results, we believe that the modified Sharpe ratio is a good measure to rank the performance of hedge fund classifications.

In Table 9 we identify the ‘‘champion hedge funds’’. The score implies the number of times an efficient fund has been part of an inefficient hedge fund’s reference set as a result of BCC efficiency analysis. As the frequency of a hedge fund appearing in a reference set increases, the likelihood of the fund being a good performer increases. The efficient hedge fund appearing in the most reference sets can be considered the overall ‘‘champion’’ and can help inefficient funds learn from their superior management and investment practices. As well, the reference set of a hedge fund can shed some light as to why a fund is performing poorly and display potential improvements in its weak areas. The 1997–2001 champion is the Prime Advisors Fund; the 1999–2001 champion is the Lafayette Europe Fund, both funds of hedge funds.

Table 6
"Spearman R" correlation analysis rankings of all hedge funds BCC vs. cross- vs. super-efficiency

Classification	BCC efficiency vs. cross-efficiency		BCC efficiency vs. super-efficiency		Cross-efficiency vs. super-efficiency	
	1997–2001	1999–2001	1997–2001	1999–2001	1997–2001	1999–2001
Funds of hedge funds	0.913** (<0.0001)	0.870** (<0.0001)	1.000** (<0.0001)	0.999** (<0.0001)	0.912** (<0.0001)	0.867** (<0.0001)
Sector	0.748** (<0.0001)	0.858** (<0.0001)	0.990** (<0.0001)	0.981** (<0.0001)	0.706** (<0.0001)	0.833** (<0.0001)
Global macro	0.813** (<0.0001)	0.854** (<0.0001)	0.988** (<0.0001)	0.982** (<0.0001)	0.783** (<0.0001)	0.816** (<0.0001)
Global emerging	0.958** (<0.0001)	0.415* (0.011)	0.994** (<0.0001)	0.860** (<0.0001)	0.963** (<0.0001)	0.509** (0.002)
Global established	0.835** (<0.0001)	0.841** (<0.0001)	1.0000** (<0.0001)	0.999** (<0.0001)	0.833** (<0.0001)	0.833 (<0.0001)
Event driven	0.741** (<0.0001)	0.660** (<0.0001)	0.990** (<0.0001)	0.988** (<0.0001)	0.729** (<0.0001)	0.656** (<0.0001)
Global international	0.730** (<0.0001)	0.859** (<0.0001)	0.995** (<0.0001)	0.979** (<0.0001)	0.704** (<0.0001)	0.804** (<0.0001)
Market neutral	0.931** (<0.0001)	0.953** (<0.0001)	1.0000** (<0.0001)	0.961** (<0.0001)	0.930** (<0.0001)	0.911** (<0.0001)

* Significant at the 0.05 level (one-tailed).
** Significant at the 0.01 level (one-tailed).

Table 7
"Spearman R" correlation analysis rankings of all hedge funds BCC, cross- and super-efficiency vs. compounded returns

Classification	BCC efficiency vs. compounded return		Cross-efficiency vs. compounded return		Super-efficiency vs. compounded return	
	1997–2001	1999–2001	1997–2001	1999–2001	1997–2001	1999–2001
Funds of hedge funds	0.687** (<0.0001)	0.791** (<0.0001)	0.834** (<0.0001)	0.929** (<0.0001)	0.685** (<0.0001)	0.786** (<0.0001)
Sector	0.638** (<0.0001)	0.685** (<0.0001)	0.803** (<0.0001)	0.823** (<0.0001)	0.598** (<0.0001)	0.660** (0.0001)
Global macro	0.673** (<0.0001)	0.467* (0.011)	0.790** (<0.0001)	0.246 (0.095)	0.743** (<0.0001)	0.359* (0.026)
Global emerging	0.559** (<0.0001)	0.166 (0.190)	0.790** (<0.0001)	0.246 (0.095)	0.743** (<0.0001)	0.357* (0.026)
Global established	0.657** (<0.0001)	0.600** (<0.0001)	0.831** (<0.0001)	0.636** (<0.0001)	0.655** (<0.0001)	0.594** (<0.0001)
Event driven	0.285** (0.007)	0.187 (0.056)	0.471** (<0.0001)	0.544** (<0.0001)	0.277** (0.009)	0.180 (0.063)
Global international	0.264 (0.112)	0.385* (0.035)	0.608** (0.001)	0.647** (<0.0001)	0.245 (0.130)	0.321 (0.068)
Market neutral	0.861** (<0.0001)	0.738** (<0.0001)	0.927** (<0.0001)	0.784** (<0.0001)	0.861** (<0.0001)	0.711** (<0.0001)

* Significant at the 0.05 level (one-tailed).
** Significant at the 0.01 level (one-tailed).

Cross-efficiency displays the scores that each hedge fund would achieve by using the optimal weights for each other hedge fund as generated by the DEA analysis. Large differences in the relative scores could indicate that each classification specializes in diverse things, for example, the percentage of the hedge fund

Table 8
"Spearman R" correlation analysis rankings of all hedge funds Sharpe and modified Sharpe vs. compounded returns

Classification	Modified Sharpe vs. compounded return		Sharpe vs. compounded return	
	1997–2001	1999–2001	1997–2001	1999–2001
Funds of hedge funds	0.621** (<0.0001)	0.455** (<0.0001)	0.710** (<0.0001)	0.509** (<0.0001)
Sector	0.788** (<0.0001)	0.862** (<0.0001)	0.799** (<0.0001)	0.858** (<0.0001)
Global macro	0.717** (<0.0001)	0.720** (<0.0001)	0.938** (<0.0001)	0.968** (<0.0001)
Global emerging	0.889** (<0.0001)	0.799** (<0.0001)	0.890** (<0.0001)	0.845** (<0.0001)
Global established	0.686** (<0.0001)	0.757** (<0.0001)	0.819** (<0.0001)	0.890** (<0.0001)
Event driven	0.482** (<0.0001)	0.382** (<0.0001)	0.552** (<0.0001)	0.596** (<0.0001)
Global international	0.909** (<0.0001)	0.890** (<0.0001)	0.944** (<0.0001)	0.958** (<0.0001)
Market neutral	0.305** (<0.0001)	0.173* (0.025)	0.500** (<0.0001)	0.487* (0.025)

* Significant at the 0.05 level (one-tailed).
** Significant at the 0.01 level (one-tailed).

Table 9
Champion hedge funds

Hedge fund	Reference set	Classification
Champion hedge funds 1997–2001		
Halcyon Special Situations	44	Event driven
Prime Advisors Fund Ltd	157	Fund of hedge funds
Van Eck Global	23	Global emerging
Seminole Capital Partners	89	Global established
Caxton Gam	14	Global macro
Artic Hedge Fund	20	Global international
KCM Biomedical	25	Sector
Atlantis Capital Management	94	Market neutral
Champion hedge funds 1999–2001		
Twin Securities	49	Event driven
Lafayette Europe Fund	122	Fund of hedge funds
Ashmore Russian Debt	12	Global emerging
Circle T Partners	37	Global established
Caxton Gam	14	Global macro
Artic Hedge Fund	20	Global international
KCM Biomedical	19	Sector
Clarion Offshore Fund	88	Market neutral

strategies within a FOF could be different. The higher the cross-efficiency score implies the fund has achieved the highest average by its peers. In other words the fund has performed well in all areas. [6]

[6] The Babe Ruth analogy is a classic example. Babe Ruth was a great home run hitter and hit more than double the home runs of any other baseball player, therefore no weight was put on the output of home runs. Therefore, using their weight on his data gave him low scores and Ruth wound up with a cross-efficiency score of 62. In terms of BCC efficiency he would have achieved a score of 100, but if he was to be compared to other players on the team he could not have been an all-around player thus making his cross-efficiency score low compared to a good all-around player. Recently, in a numerical study of baseball batters, Babe Ruth did poorly even in his prime years (1920 and 1921) because he dominated the other hitters, but the number of singles, doubles and triples by other baseball players were more valuable than Babe Ruth's home runs (Anderson et al., 1998). This is related to the Babe Ruth phenomenon, where other hitters put greater weights on doubles and triples so as to make Babe Ruth look bad.

Finally, if we look at the individual funds, we observe that in all classifications there are fewer efficient funds in the 5-year as opposed to the 3-year period. The reason is that funds during the 1997–2001 period could have experienced a tremendous amount of increased risk owing to Russian ruble crisis of August 1998. It is also surprising to see that the fund of hedge funds, and market neutral classifications contain the least number of efficient funds in both examination periods when compared to the total number of funds (as a percentage) in their respective categories. The abnormality could be partly due to the high kurtosis (fat tails) in each of the above classifications exposing them to extreme market events.

The large majority of efficient funds during the 5-year period are also efficient in the 3-year period, providing an indication that some hedge funds are able to control for risk with a greater amount of accuracy than other funds. The large majority of funds that were efficient in both periods had higher cross-efficiency scores in the 5-year period.

5. Conclusion

This paper demonstrates that DEA can be used as an alternative selection tool to assist pension funds, institutional investors, FOF managers and high net worth individuals in selecting efficient hedge funds. We believe DEA is an excellent complement to other risk-adjusted measures and can present a more complete picture of hedge fund performance appraisal. The empirical results validate that even when using non-normal returns in a risk–return framework DEA can provide reliable results. Hedge fund performance evaluation using DEA is important because it allows investors to properly (or correctly) identify superior performing funds because using conventional risk-measurement techniques can be misleading.

Future research using other DEA models could examine managed futures classifications. It would also be interesting to measure the efficiency of various hedge fund indices from database vendors, such as Hedge Fund Research (HFR), EACM, ALTVEST, and TASS.

Finally, other DEA approaches can also be used to characterize the performance of hedge funds. For example, one can use the DEA-based benchmark models to compare the performance of hedge funds in different groups. One can also use the recent development of super-efficiency in Chen (in press) to fully rank hedge fund performance.

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