Implications of Higher Order Risk Factors for Hedge Fund Performance

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Abstract

This paper investigates the performance of hedge funds adjusted for higher order risk factors. Traditional risk-adjusted performance measures are subject to size distorted in the presence of skewness and kurtosis. A residual augmented least squares approach to model higher order risk moments in returns allows us to estimate a robust risk-adjusted performance measure for hedge funds. In a comparison of two styles of hedge funds, emerging market hedge funds are found to generate superior performance with higher positive significant alpha values than long/short equity funds.

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Abstract: This paper investigates the performance of hedge funds adjusted for higher order risk factors. Traditional risk-adjusted performance measures are subject to size distorted in the presence of skewness and kurtosis. A residual augmented least squares approach to model higher order risk moments in returns allows us to estimate a robust risk-adjusted performance measure for hedge funds. In a comparison of two styles of hedge funds, emerging market hedge funds are found to generate superior performance with higher positive significant alpha values than long/short equity funds.

I. Introduction

In recent times there has been a shift away from traditional active strategies towards alternative investments, such as hedge funds, following evidence that mutual funds underperform passive investment strategies (Ackermann, McEnally and Ravenscraft, 1999; Liang, 1999).[1] Hedge funds use active management skills to earn positive returns on capital regardless of market direction.

Traditionally hedge funds were established to minimise risks by taking long and offsetting short positions, they now pursue a variety of strategies attempting to profit from observed market inefficiencies. Evidence shows that while some hedge fund strategies are driven by the same market factors as traditional investments, others derive returns from short-run market pricing inefficiencies and liquidity requirements (Ackermann *et al.*, 1999).

Previous assessment of hedge fund performance used traditional single index or multi-factor models based on the mean-variance criterion. One of the main assumptions underlying the mean-variance framework is the normal distribution of returns. However, recent research has shown that hedge funds have different distributions of returns from traditional investments and conventional equilibrium models are not suitable for measuring performance (see, Brooks and Kat, 2002; Kat and Lu, 2002; Lo, 2002; Lubochinsky, Fitzgerald and McGinty, 2002; Gregoriou and Gueyie, 2003; Agarwal and Naik, 2004; Capocci and Hübner, 2004; Hung, Shackelton and Xu, 2004; Chung, Johnson and Schill, 2006; Ding and Shawky, 2007).

In the presence of higher order return moments of skewness and kurtosis, the mean-variance approach will distortion the inherent risk in hedge funds. In particular, the standard deviation (or variance) is not the only risk within hedge funds – investors are also exposed to the risks of skewness and kurtosis. Moreover, the skewness and kurtosis cannot be diversified away through funds of funds. Since non-normality is an issue for hedge funds, the inclusion of skewness and kurtosis risk measures in the model of the performance is necessary. We capture these higher order risk factors using a residual augmented least squares (RALS) approach (see Im, 2001; Im and Schmidt, 2001).

This paper considers two types of hedge fund strategies, namely emerging markets and long/short equity. We concentrate on these two categories because (i) according to the TASS database, the majority of the top 30 performing funds from the past five years are from these asset classes. (ii) Long/short equity strategy was the first hedge fund created by Alfred W. Jones, and it will be intriguing to see whether the fundamental focus of the funds to hedge market risk is being adhered to today.

Developing a model that incorporates higher order risks will contribute to current research in hedge funds as it will provide a robust risk-adjusted performance measure. This research first applies the residual augmented least squares approach to traditional performance measures of a "fund of funds", with funds generated by deciles from the hedge fund database based on mean return performance. The model generates an alpha performance measurement which incorporates the higher order risk factors and assesses the resulting performance distortion arising from skewness and kurtotsis. This work provides a novel and necessary foundation for future risk management and portfolio management in the hedge fund area.

The next section outlines a brief account of the fund performance literature. Section 3 presents the methods of analysis in modelling risk and return in hedge funds, including modelling higher order moments. Section 4 provides details of the data and an overview of the performance models used in the study. The empirical results and analysis are presented in Section 5. The individual performance of the funds is then examined for both emerging market and long/short equity funds in Section 6. Section 7 concludes the paper.

II. Fund Performance

The objective of performance analysis is to distinguish skilled investment managers from those whose success is due to chance (luck). While single index models, such as CAPM, were traditionally used to assess performance (Jensen, 1968), there has been a shift in recent times towards multi-factor models, which incorporate factors such as the size and book-to-market factors of Fama and French (1993) and Carhart's (1997) momentum factor. More recently, performance analysis has tended to incorporate higher order risk factors. Bollen and Busse (2001) show that higher order moments should be included when measuring returns and that fund managers possess more stronger performance (coming from market timing ability) than had previously been documented.

Numerous researchers have investigated the performance of hedge funds, and their findings differ widely. Due to their dynamic activity, accurately measuring the performance of hedge funds is difficult. While earlier research was mainly centred on traditional performance measures, such as Jensen's alpha, recent literature has shown a shift towards more technical multi-factor models due in part to the non-normality and serial correlation of returns (see, for example, Getmansky, Lo and Makarov, 2004; Chan, Getmansky, Haas and Lo, 2005; Ding and Shawky, 2007) .

Recent research into the performance of hedge funds has included reference to the presence of statistically significant higher order moments (see for example, Fung and Hsieh, 1997; Agarwal and Naik, 2004; Kat and Lu, 2002; Lubochinsky *et al.*, 2002; Kat and Amin, 2003; Clark and Winkelmann, 2004) and serial correlation (see, for example, Brooks and Kat, 2002).

In general hedge funds have tended to show superior risk-adjusted performance relative to mutual funds and standard market indices (see for example, Fung and Hsieh, 1997; Ackerman *et al.*, 1999; Agarwal and Naik, 2000a, 2000b; Liang, 2001; Lubochinsky *et al.*, 2002). However, there are a number of factors that renders accurate assessment of the performance of hedge funds difficult, including, a lack of performance history, the dynamic nature of the trading strategies, and the potential for limitless arbitrage (Fung and Hsieh, 2000a).

Hedge fund databases are commonly used as a benchmark for performance and as a means of gaining greater understanding of the funds. Since most of these indices were not present before the 1990s, various characteristics of the databases lead to reporting biases that tend to involve overstatement of hedge fund returns. For this reason, references to biases, which include survivorship bias, selection bias and instant history bias is common. For example, Brown, Goetzmann, Ibbotson and Ross (1999) report a survivorship bias of 3 percent a year for hedge funds.

Furthermore, funds tend to register themselves with databases only when they have good performance. As this may be a few years after inception, returns generated during the incubation period will be backfilled.[2] Fung and Hsieh (2000b) reported that this instant history bias is 1.4 percent a year.

Recent performance analysis of hedge funds identify non-normality as a key feature of their returns and question the validity of previous studies that measured performance using traditional metrics such as the Jensen's alpha and Sharpe ratio. Agarwal and Naik (2004) and Gupta, Cerrahoglu and Daglioglu (2003) have suggested approaches to overcome this problem. For example, Gupta *et al*. (2003) tested the performance using a generalised method of moments (GMM) estimation and Agarwal and Naik (2004) used an extended Value-at-Risk model, namely mean-conditional VaR. Furthermore, the alphas generated from traditional models whether single- or multi-factor models were found to be insignificantly different from each other (Gupta *et al.*, 2003).

Increasing the number of funds in a portfolio of hedge funds leads to lower standard deviation, lower skewness and increased correlation with the stock market (Kat and Amin, 2003). However, due to the significant higher order risk moments, hedge funds do not provide useful diversification benefits when combined with equity only portfolios (Kat and Lu, 2002). While only a small number of funds need be so combined as to obtain a more efficient risk-return profile, the resulting improvement in the efficient frontier has a corresponding increase in kurtosis and a decrease in skewness (Kat and Amin, 2003). Therefore, using only ex-post variance measures in a mean-variance portfolio analysis, that includes hedge funds, will over-allocate to hedge funds and overestimate the benefits to be expected from including hedge funds in an investment portfolio.

There are three main findings of the literature: (i) non-linear payoffs are a key feature of hedge fund strategies; (ii) the mean-variance optimal framework can underestimate losses as a result of significant kurtosis; and (iii) reported performance during last decade is not representative of long-term performance as mean returns are likely to be lower and mean standard deviations significantly higher (see, Agarwal and Naik, 2004).

III. Risk and Return of Hedge Funds

A key difference between risk in hedge funds and that in mutual funds stems from the different definitions of risk. In general, hedge funds define risk as the loss of capital whereas mutual funds assess risk as tracking error relative to a benchmark. The traditional measurement of investment risk is standard deviation (or variance), measures the spread of the distribution about the mean and hence gives a picture of the uncertainty of the returns. Related to this is the Sharpe ratio (1966) to rank portfolio performance and is traditionally used to assess hedge fund performance.

The accuracy of the Sharpe ratio rests on the statistical properties of returns, and high volatility will impact negatively on its accuracy. Since the return characteristics of hedge funds are very different from those of mutual funds, a comparison of the Sharpe ratios between the two investment strategies should be carried out with caution, as the interpretation of the ratios must incorporate information about the investment style. Assumptions on the return-generation process that underlie the Sharpe ratios can lead to inaccuracies. Positive serial correlation of monthly returns can lead to overstatements of the Sharpe ratios by as much as 65 percent, and negative serial correlation can yield comparable understatements (see, Lo, 2002). This will result in inconsistent rankings across hedge funds with different styles and objectives.

A more common approach in recent times is to assess risk-adjusted performance using a multi-factor model similar to the Fama-French-Carhart model:

[1] $$(R_{jt} - R_{ft}) = \alpha_j + \beta_{1j}(R_{mt} - R_{ft}) + \beta_{2j}SMB_t + \beta_{3j}HML_t + \beta_{4j}UMD_t + u_{jt}$$

where R_{jt} is the return on portfolio j at time t; R_{ft} is the risk-free rate, for example the one-month Treasury bill rate; R_{mt}, the market return; α_j is alpha, the measure of the manager skill; β_j is the sensitivity of the portfolio to the market; SMB_t is the large versus small market capitalisation stocks factor; HML_t is the value versus growth stocks factor, UMD_t is the one-year return momentum versus contrarian stocks factor; and u_{jt} is the error term. A more detail account of this model is given in Fama and French (1993) and Carhart (1997).

Return Persistence and Serial Correlation

While traditional investment vehicles are highly liquid, hedge funds are renowned for their long lock-up period and severe early redemption penalties. These exit structures are in place to protect the underlying investments, which in many cases are illiquid and very difficult to measure accurately. Since the valuations of the underlying assets will not change from month to month if they are both illiquid and not traded on an exchange, the assessment of their value will be correlated in successive months. The simplest persistence test is a month-by-month regression of past returns on current returns (see, Getmansky *et al*., 2004; Chan *at al*., 2005).

[2] $$\overline{R}_{jt} = \alpha_j + \beta_{1j}\overline{R}_{mt} + \beta_{2j}SMB_t + \beta_{3j}HML_t + \beta_{4j}UMD_t + \beta_{5j}\overline{R}_{jt-1} + u_{jt}$$

where $\overline{R}_{jt} = (R_{jt} - R_{ft})$ is excess fund j return at time t, $\overline{R}_{mt} = (R_{mt} - R_{ft})$ is the excess market return at time t.

The Residual Augmented Least Squares Approach to Hedge Fund Performance

While the presence of higher order moments in hedge funds has been ascertained, the literature does not provide a suitable model to adjust for them. In order to measure risk-adjusted returns accurately, it is important to incorporate the higher order moments into the performance model. Investors will demand compensation for the additional risk to which they are exposed as a result of the significant higher order moments, that is negative skewness and positive kurtosis. In addition, since the non-normality of the returns introduces misspecification into traditional performance models (such as [1]), the resulting performance measures are distorted.

The residual augmented least squares (RALS) approach, first introduced by Im(1996), extends a linear regression models to include the higher order moments, namely skewness and kurtosis. Consider a linear regression model:

[3] $$y_t = \phi' z_t + u_t$$

where y_t is the dependent variable at time t, $z_t = (1 \;\; x_t')'$, x_t is a (k – 1)×1 vector of time series observed at time t, $\phi = (\alpha \;\; \beta')'$ is the parameter vector where α is the intercept and β is the (k – 1)×1 vector of parameters of interest, and the residuals u_t are iid with distribution function symmetric around zero.

Im (1996, 2001) is concerned with developing an estimator which is robust to skewness and kurtosis in the distribution of the error term. One of the underlying assumptions of this equation is that the residual term, u_t, is normally distributed and independent of the other variables.

[4] $E\,[\,z_t\;u_t\,] = 0$

Skewness implies a non-zero standardized third central moment, so that

[5] $E\,(u_t^3 - \sigma^3) = E\,[u_t\,(u_t^2 - \sigma^2)] \neq 0$

which implies that $(u_t^2 - \sigma^2)$ is correlated with u_t but not with the regressors, since z_t and u_t are independent. Similarly, excess kurtosis implies that the standardized fourth central moment of the series exceeds three:

[6] $E\,(u_t^4 - 3\sigma^4) = E\,[u_t\,(u_t^3 - 3\sigma^2\,u_t)] \neq 0$

implying that $(u_t^3 - 3\sigma^2\,u_t)$ is correlated with u_t but not with the regressors, since (again) z_t and u_t are independent.

Since the least squares procedure minimises squared deviations, it places a relatively high weight on outliers, and in the presence of errors that exhibit non-normal distribution as in the case of hedge funds, the resulting ordinary least squares (OLS) coefficients will be not be robust. While Gupta *et al.* (2003) used a generalised method of moments (GMM) method to overcome this non-normality issue, RALS can also be interpreted as a GMM estimator that incorporates the additional moment conditions as in [4], [5], and [6]. Im (1996, 2001) and Im and Schmidt (2001) suggests a two-step estimator which can be simply computed from OLS applied to [3] augmented by the vector of covariates $\hat{w}_t = [(\hat{u}_t^3 - 3\hat{\sigma}^2\,\hat{u}_t)\;\;(\hat{u}_t^2 - \hat{\sigma}^2)]'$:

[7] $y_t = \alpha + \beta'\,z_t + \gamma'\,\hat{w}_t + e_t$

where $\hat{u}_t$ denotes the residual and $\hat{\sigma}^2$ is the standard residual variance estimate obtained from OLS applied to [3]. When both the regressors and the regressand are stationary, the resulting RALS estimator of $\phi = (\,\alpha\;\;\beta'\,)'$, say β^*, is given by $\beta^* = (\tilde{X}'M_{\tilde{W}}\tilde{X})^{-1}\tilde{X}'M_{\tilde{W}}Y$ and $\alpha^* = \beta^*\big|z_t = 1'$ where the idempotent matrix $M_{\tilde{W}}$ is $M_{\tilde{W}} = I_T - \tilde{W}'(\tilde{W}'\tilde{W})^{-1}\tilde{W}$ where I_T is the $T \times T$ identity matrix and $\tilde{N} = (\tilde{n}_1\tilde{n}_2\ldots\tilde{n}_T)'$, $n_t = n_t - T^{-1}\sum_1^T n_t$ for $(N,n) = (X,x),(Y,y),(W,w)$ and $t = 1,\ldots T$. The asymptotic distribution given by $\sqrt{T}\,(\,\beta^* - \beta\,) \rightarrow N\,[0,\;\sigma_A^2\,\mathrm{Var}(\,x_t\,)^{-1}]$, where

$$\sigma_A^2 = \sigma^2 - \frac{\mu_3^2(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - 2\mu_3(\mu_4 - 3\sigma^4)(\mu_5 - 4\mu_3\sigma^2) + (\mu_4 - 3\sigma^4)^2(\mu_4 - \sigma^4)}{(\mu_4 - \sigma^4)(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - (\mu_5 - 4\mu_3\sigma^2)^2}$$

and μ_i denotes the *i*-th central moment of u_t. In practice, σ_A^2 can be consistently estimated by replacing each of the μ_i with the corresponding sample moments, using the OLS residuals, yielding $\hat{\sigma}_A^2$, and the covariance matrix of β^* can be consistently estimated by $V(\beta^*) = \hat{\sigma}_A^2(\tilde{X}'M_{\tilde{W}}\tilde{X})^{-1}$. The efficiency gain from employing RALS as opposed to OLS can be gauged from the statistic $\hat{\eta} = \hat{\sigma}_A^2 / \hat{\sigma}^2$ (which is small for large efficiency gains). In the presence of normal error terms, RALS is asymptotically identical to the OLS estimator and there is no efficiency gain.

Although the basic single-index model has already been extended to include the additional risk factors as outlined by Fama and French (1993), and Carhart (1997), as in [1], there is considerable evidence that hedge funds have non-normal distribution of returns. To avoid size distortion this non-normality must be accounted for in modelling to permit a robust measurement of fund performance. Using the residual augmented least squares approach, the multi-index model is extended to include the third and fourth higher order risk moments as shown in [7] and we can compute a RALS α, given by α^*.

IV. Data and Summary Statistics

Monthly data for the 157 long/short equity hedge funds and 96 emerging market funds were obtained from the TASS database for the period 1999:1 through to 2004:12. Returns are computed as the change in net asset value (NAV) during the month divided by the net asset value at the beginning of the month. Returns used are net of management fees, incentive fees and other fund expenses. In practice, reported returns may differ from investor returns due to redemption fees and bid and ask spreads. We use the CRSP NYSE/AMEX value-weighted index as the market portfolio. To capture the effects of size, book-to-market value and momentum are from Ken French's web pages.[3]

Long/short equity (LS) funds are the most common style of hedge fund, representing 45% of the hedge funds in existence. The manager attempts to profit on both long and short stock positions independently, or from the relative superior performance of long positions against short positions. This strategy may be expected to be less volatile than alternative strategies, which hold long-only or short-only positions.

Emerging market (EM) funds focus on less mature markets, investing in securities of companies or sovereign debt of developing countries, where there is potential for significant future growth. Most emerging market countries are located in Latin American, Eastern Europe, Asia or the Middle East. Funds mainly hold long-only positions as many emerging markets do not permit short selling and many derivative products are not available. In light of these constraints, emerging market funds would be expected to be more volatile than most other styles.

A preliminary analysis of the risks and returns of the two hedge fund categories using the basic Sharpe ratio, based on deciles of funds reveals that the top 7 deciles in the LS fund category and the top 8 EM fund deciles out-performed the market (see Table 1). This result is similar to many pervious hedge fund performance studies, for example, Lubochinsky *et al.* (2002) and Agarwal and Naik (2000a, 2000b). The EM strategy has a higher return on average than LS funds. The risk, as measured by standard deviation, is also higher for the EM funds than for LS funds. Interestingly, the market on average has a higher standard deviation than the average EM and LS fund. Similar to Kat and Lu (2002), the return data show that both EM and LS funds have a relatively close relationship with the market.

V. Empirical Results and Analysis

We investigate the performance of EM and LS hedge funds using the single factor capital asset pricing model (CAPM), with the results presented in Table 5. The computed $\overline{R}^2$ indicate a strong significant relationship between fund returns and market returns; this is particularly evident in the case of EM funds. However, the relationship decreases as we consider stronger performing funds. This latter finding is consistent with Fung and Hsieh (1997) and Liang (1999) who reported lower correlation with the market due to the dynamic trading strategies of high performing hedge funds compared with traditional buy-and-hold strategies.

The top 7 deciles for both EM and LS funds exhibit statistically significant positive Jensen alphas. However, the bottom decile exhibits a significant negative alpha. The reported, positive alpha is consistent with the results of Brown *et al*. (1999) and Agarwal and Naik (2000a, 2000b); however, more recent research by Clark and Winkelmann (2004) finds that the estimated alpha for LS funds is not statistically different from zero.

Investors seek positive skewness, where the portfolios have a higher probability of large payoffs. Negative skewness will requires higher returns as compensation for the additional risk taken. Consistent with Kat and Amin (2003), Kat and Lu (2002), Lubochinsky *et al.* (2002) and Agarwal and Naik (2004) and others, both fund strategies show significant evidence of non-normality in returns (see Table 2). The Jarque-Bera (1987) statistic rejects the null hypothesis for normality.

Multi-Factor Analysis

On the basis of the regression results from [2], the EM funds showed positive sensitivity only to the size factor, SMB, in five deciles, two of which were significant at a 10% level (see Table 3). The value and momentum factors, HML and UMD respectively, were overall statistically insignificant with only one of the deciles, in the case of HML, showing significance at a 10% level. This was also mirrored by only a small change in the R-squared value from the case of the CAPM.

In contrast, LS funds show a substantial increase in explanatory power, due mainly from positive and statistically significant SMB and UMD factors. This result is similar to Agarwal and Naik (2002) who reported a statistically significant SMB factor. A positive exposure to the SMB factor suggests that the investment manager bought undervalued stocks and offset market risk by short-selling stocks. The positive exposure to value indicates that managers were short growth stocks in the same period. This is expected as the growth stocks declined after the technology bubble burst in early 2000.

In using a multi-factor model, Fung and Hsieh (1997) and Liang (1999) report positive alphas for both EM and LS funds. While our results generated an average $\overline{R}^2$ of 46%, Fung and Hsieh (1997) report a lower $\overline{R}^2$ of 25% for the hedge fund returns.

Persistence in Hedge Fund Returns

The multi-factor model was extended to include the lagged dependent variable, as in [2]. The regression results indicate that the lagged variable is statistically significant in the case of both strategies in nine out of ten deciles, mainly at a 1% significance level (see Table 4).[4] This indicates that there is persistence in the returns of the funds and the variability of reported returns is carried forward. Moreover, the alphas show some convergence towards zero, with negative values becoming less negative and the larger positive values shrinking.

The RALS Model of Hedge Fund Performance

We estimate [7] using the multi-factor model [2] and report the results in Table 5. The addition of the higher order risk factors, namely skewness and kurtosis, has resulted in a higher $\overline{R}^2$ of between 75% and 90% across all funds. Moreover, the residual augmented least squares performance measure α^* shows on average some convergence towards zero.

EM funds exhibit positive and significant α^* values for the top 6 deciles and the top 7 deciles for the LS funds, although the latter funds are of a smaller magnitude. From the residual augmented least squares approach, the kurtosis factor is $E\,[u_t\,(u_t^3 - 3\,\sigma^2\,u_t)]$ and is modelled by means of the variable $(\hat{u}_t^3 - 3\,\hat{\sigma}^2\,\hat{u}_t)$ and the estimated parameter γ_1. This higher order moment is statistically significant at the 1 percent level for both fund strategies in all deciles. Since the presence of kurtosis indicates that the tails of the return distribution are wider than normal, the traditional lease squares approach to [2] introduces a size distortion for α. The existence of outliers, whether in the form of highly positive or negative results, will overstate the performance reports if not accounted for. These results are consistent with previous findings, such as Lubochinsky *et al.* (2002) and Agarwal and Naik (2004), who reported significant tail risk in hedge funds.

The skew factor is $E\,[u_t\,(u_t^2 - \sigma^2)]$ is modelled by means of the variable $(\hat{u}_t^2 - \hat{\sigma}^2)$ and parameter γ_2. Table 5 reports that the top deciles in the EM funds exhibit significant negative weighting attached to the skew factor. Thus, a fund that exhibits negative skew will require a positive risk premium. Similar results are found for LS funds but the relationship is less significant across deciles.

The efficiency ratio $\hat{\eta}$ reported in Table 5 shows that the residual augmented least squares approach leads to substantial efficiency gains in modelling the return generating process and thus the performance measurement α^* is more appropriate than the ordinary least squares α as it less likely to suffer from size distortion. In general, the residual augmented least squares approach to modelling single- and multi-factor models when returns exhibit higher order moments generates a more robust performance measurement.

VI. Individual Fund Performance

In this section we apply the residual augmented least squares approach to the returns of individual funds and using the single factor CAPM $\overline{R}_{jt} = \alpha_j + \beta_j \overline{R}_{mt} + u_t$ rank their resulting performance. We also compare α^* to the ordinary least squares CAPM α. The inclusion of these higher order risk factors provides a more robust picture of fund performance and adjust performance for the size distortion arising from the ordinary least squares approach.

Emerging Market Funds

The individual EM funds display statistically significant positive α^* values at a 5 percent level of significance for 74 of the 96 funds. The distribution of α^* is smaller and its mean is closer to zero than the ordinary least squares α distribution. The average monthly α^* for EM funds is 1.63% and is significantly different from zero at the 1 percent level of significance.

The top 15 and bottom 5 α^* EM funds are detailed in Table 6, and their relative rankings are compared with the ordinary least squares α.[5] This shows that the rankings can be substantially different depending on the least squares approach taken. For example, funds EM51 and EM44 are ranked 5th and 15th on the basis of α^*, respectively, compared to 51st and 64th on the basis of α. Table 6 also shows that the highest performing fund by α^* is ranked only 7th by α. A similar result is obtained for most funds with poor performance, which differ with a stark example of the 11th ranked fund based on α, ranked as 93rd under α^*.

These significant differences have considerable implications for the evaluation procedures used, and show that traditional ordinary least squares single factor CAPM will distort performance of funds. Since negative skewness and positive kurtosis must be rewarded, it would be expected that in their presence abnormal performance would be lower, i.e., a lower alpha.

The Spearman's rank correlation test, when used to compare the ranking based on α and α^*, yielded a coefficient value of 0.67. This indicates that there is a significant positive correlation between the alternative approaches to ranking performance. While there are outliers, the majority of comparative alpha values are within ten ranking places of each other.

Long/Short Equity Funds

On average the monthly mean return for the LS funds is 0.95% and the average Jensen's alpha (α) is 0.75%. As for the EM funds, the α^* values have converged somewhat towards zero and generally smaller than α for the LS funds. This shows that by incorporating the risk of the higher order moments using the residual augmented least squares approach, abnormal returns and skill of the fund managers is distorted.

The residual augmented least squares approach indicates that only 88 of the 157 LS funds display statistically significant α^* values at a 5 percent level of significance. The range of significant α^* values is 2.99% for the highest and –4.1% for the lowest, and correspond to average monthly returns of 5.14% and –0.42%, respectively. In general α^* are considerably lower than α, especially for high performing LS funds. The positive alpha values are consistent with previous results of Brown *et al.* (1999), Liang (1999), Fung and Hsieh (2001), and Agarwal and Naik (2000).

The extent of the distortion in ranking under ordinary least squares can be seen in Table 7 – for example, for funds LS034 and LS144, α ranks them as 135th and 129th, respectively, whereas α^* places them in 4th and 14th position. For the worst performing funds (LS116), the 2nd best LS fund under α is ranked as 2nd worst under α^*. In contrast, LS034 fund has gone from a ranking of 135th under α to 4th under α^*. The risk of higher order moments is clearly a fundamental factor in distorting risk-adjusted performance.

In the case of the LS funds, the Spearmann rank correlation coefficient between rankings based on α and α^* is 0.49. This shows a substantially lower correlation than the EM case, indicating that few funds have remained in the same ranking when the more robust residual augmented least squares approach is used. In fact only 3 of the 157 funds remained in the same rank.

LS funds show lower risk-adjusted alpha performance measurements (whether α or α^*) than EM funds. Diversity of trading approaches involving degrees of leverage and the choice of financial instruments may explain performance differences between managers. The differences in performance ranking in the LS funds are considerable for the sample in question, particularly in the extremes.

The substantial change in rankings in the case of both EM and LS strategies shows that both fund strategies have significant higher order moments that are present in individual funds and also in "funds of funds", which partially accounts for the abnormal returns. The simple single factor CAPM estimated by ordinary least squares is not robust and fails to capture non-normality that distorts the risk-adjusted performance of hedge funds. In general, hedge funds exhibit strong positive alphas even after accounting for the higher order moments. However, individual ranking can substantially change and caution should be used by investors in using the basic Jensen's alpha (α) in their allocation decision – this is especially the case when considering LS funds.

VII. Conclusion

Hedge funds are increasingly becoming a conventional investment vehicle as the number of investors and investment managers entering the arena grows. While traditional funds have underperformed the market indices, hedge funds by consistently reporting excess returns, have become more popular with investors. As a result the analysis of the performance returns of hedge funds is currently the focus of a considerable amount of research. In this paper the performance of deciles of "fund of funds" and individual funds are examined using a residual augmented least squares approach to assess risk-adjusted performance. This approach accounts for higher order moments in returns that might distort performance when estimated using ordinary least squares and provides a more robust risk-adjusted performance measure for hedge funds.

Recent empirical evidence has shown that hedge funds have non-normal return distributions with significant higher order moments (see for example, Kat and Lu, 2002; Lubochinsky *et al.*, 2002; Agarwal and Naik, 2004). While previous studies relied on traditional measurements, in the presence of higher order moments these measures are distorted. For example, Lo (2002) shows that the Sharpe ration overstates the true performance in the presence of higher order moments. This paper goes beyond previous performance assessments, providing a more robust appraisal of returns by incorporating higher order moments. The multi-factor model was estimated by residual augmented least squares, with the adjusted model showing a substantial increase in explanatory power. The efficiency ratio indicates a vast improvement in the performance model. Incorporating higher order risk factors has yielded results superior to those traditionally used in hedge fund analysis.

When the residual augmented least squares approach is applied to individual funds, emerging market funds are the superior investment choice compared to long/short equity funds. On average, emerging market funds generate higher risk-adjusted returns with higher positive significant alpha values than long\short equity funds. There are a variety of possible explanations for this. First, emerging market funds are a very small section of the hedge funds market; as such the market opportunities may not yet be saturated. Since the economies and securities in developing countries have less of the readily available information required in an efficient market, there may be arbitrage opportunities in the emerging market that are no longer present in the major equity markets. Second, long/short equity strategy is the easier trading strategy to partake in, with the result that there are larger numbers of managers and distinctive returns are difficult to attain. Overall, both strategies do generate excess returns for the majority of funds, with reported significant positive residual augmented least squares alpha values for approximately 56% of long/short equity funds and 77% of emerging market funds.

Further research should include a micro-investigation into the risk factors of each individual fund. Comparing residual augmented least squares alpha values generated from a multi-index Fama, French and Carhart models with that using ordinary least squares, will give further indications of the risk characteristics of the funds.

The residual augmented least squares approach could also be used to assess the risk-adjusted performance across all strategies of hedge funds. This will provide a more robust ranking of both the strategies and the highest performing individual funds. Since non-normality is an issue in many areas of financial markets today, the residual augmented least squares model can also be applied to returns of a variety of securities and to give a more accurate picture of the risk-return profile and asset allocation than the traditional mean-variance efficient frontier.

This paper provides the foundation for future development in examining hedge fund performance. The application of the residual augmented least squares approach in the sphere of hedge funds is novel and provides a very useful framework for assessing hedge funds in the presence of higher order moments. Incorporating these additional risk factors, it confirms that hedge funds do indeed generate abnormal risk-adjusted returns.

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Table 1: Risk and Return

Decile	Mean Return (%)	Standard Deviation	Sharpe Ratio	Correlation with Market
EM1	6.187	9.306	0.665	0.488
EM2	3.774	6.254	0.603	0.604
EM3	2.867	5.263	0.545	0.652
EM4	2.349	4.900	0.479	0.633
EM5	1.802	4.368	0.412	0.696
EM6	1.308	3.631	0.360	0.699
EM7	0.849	3.342	0.254	0.631
EM8	0.425	3.233	0.131	0.674
EM9	-0.199	3.627	-0.055	0.769
EM10	-1.693	4.537	-0.373	0.710
LS1	4.564	5.702	0.800	0.572
LS2	2.528	3.791	0.667	0.680
LS3	1.854	2.731	0.679	0.453
LS4	1.388	2.542	0.546	0.577
LS5	1.067	2.419	0.441	0.531
LS6	0.758	2.624	0.289	0.635
LS7	0.442	1.962	0.225	0.759
LS8	0.024	2.609	0.009	0.668
LS9	-0.507	3.080	-0.164	0.757
LS10	-1.973	4.383	-0.450	0.760
Market	0.093	4.817	0.019	1.000

Note: The period of analysis is from January 1999 through to December 2004. EM refers to Emerging Market Funds, LS refers to Long/Short Equity Funds. Deciles are ranked from 10 to 1, with 1 being the top performers. Sharpe Ratio is the excess monthly return divided by the standard deviation. The market is value-weighted return on all NYSE, AMEX and NASDAQ stocks (from Ken French's website).

Table 2: CAPM Regression

Decile	Mean Return (%)	$\bar{R}^2$	DW	α	β	Skew	Kurt	JB
EM1	6.187	0.23	1.58	6.100†	0.943†	1.94	11.12	416.13†
EM2	3.774	0.36	1.56	3.701†	0.784†	0.43	3.27	34.30†
EM3	2.867	0.42	1.45	2.801†	0.712†	0.25	3.56	38.77†
EM4	2.349	0.39	1.42	2.289†	0.644†	0.81	5.56	100.61†
EM5	1.802	0.48	1.42	1.743†	0.631†	0.44	5.41	90.13†
EM6	1.308	0.48	1.89	1.260†	0.527†	1.14	6.94	160.09†
EM7	0.849	0.39	1.55	0.808††	0.438†	-0.12	5.12	78.82†
EM8	0.425	0.45	1.45	0.383	0.453†	-0.41	3.78	44.88†
EM9	-0.199	0.59	1.57	-0.253	0.579†	-0.63	3.14	34.34†
EM10	-1.693	0.50	1.44	-1.755†	0.668†	-0.16	2.13	13.92†
LS1	4.564	0.32	1.21	4.501†	0.678†	1.23	4.74	85.56†
LS2	2.528	0.46	1.46	2.478†	0.536†	1.36	5.70	119.67†
LS3	1.854	0.19	1.36	1.831†	0.257†	1.36	7.23	179.01†
LS4	1.388	0.32	1.58	1.360†	0.305†	2.03	9.73	333.47†
LS5	1.067	0.27	1.50	1.042†	0.267†	1.22	5.45	106.97†
LS6	0.758	0.39	1.55	0.726†	0.346†	1.57	8.25	233.77†
LS7	0.442	0.57	1.51	0.413†	0.309†	1.00	4.97	86.10†
LS8	0.024	0.44	1.87	-0.009	0.362†	1.41	9.23	279.44†
LS9	-0.507	0.57	1.91	-0.551††	0.484†	0.67	6.50	132.14†
LS10	-1.973	0.57	1.65	-2.037†	0.692†	-0.76	3.75	49.12†

Note: Refer to Table 1. The results are from estimating the single factor CAPM: $\bar{R}_{jt} = \alpha_j + \beta_j \bar{R}_{mt} + u_{jt}$. †, ††, and ††† indicate statistically significant at the 1%, 5% and 10% levels, respectively. Skew is the skewness statistic defined as $S_j = (\frac{1}{T}\sum_{t=1}^{T}(R_{jt} - R_j^d)^3)/\sigma_j^3$ and Kurt is the excess kurtosis statistic defined as $K_j = (\frac{1}{T}\sum_{t=1}^{T}(R_{jt} - R_t^d)^4)/\sigma_j^4 - 3$, where $R_j^d = (1/T)\sum_{t=1}^{T} R_{jt}$ is the average monthly return. The Jarque-Bera statistic (JB) is defined as $(T/6)(S_j^2 + 1/4K_j^2)$.

Table 3: Multi-Index Regression

Decile	Mean Return(%)	$\bar{R}^2$	DW	α	β_1	β_2	β_3	β_4
EM1	6.187	0.26	1.75	$5.824^{\dagger}$	$0.91^{\dagger}$	0.25	-0.11	0.19
EM2	3.774	0.35	1.65	$3.364^{\dagger}$	$0.85^{\dagger}$	0.20	0.18	0.05
EM3	2.867	0.42	1.48	$2.503^{\dagger}$	$0.86^{\dagger}$	0.07	$0.25^{\dagger\dagger\dagger}$	0.07
EM4	2.349	0.39	1.48	$2.100^{\dagger}$	$0.64^{\dagger}$	0.17	0.05	0.02
EM5	1.802	0.49	1.45	$1.480^{\dagger}$	$0.66^{\dagger}$	$0.19^{\dagger\dagger}$	0.14	0.01
EM6	1.308	0.50	2.00	$1.081^{\dagger}$	$0.53^{\dagger}$	$0.15^{\dagger\dagger\dagger}$	0.05	0.03
EM7	0.849	0.37	1.63	$0.748^{\dagger}$	$0.48^{\dagger}$	-0.00	0.04	0.05
EM8	0.425	0.53	1.59	0.118	$0.45^{\dagger}$	$0.22^{\dagger}$	0.08	0.03
EM9	-0.199	0.60	1.71	-0.316	$0.52^{\dagger}$	$0.12^{\dagger\dagger\dagger}$	-0.03	-0.02
EM10	-1.693	0.56	1.55	$-2.024^{\dagger}$	$0.61^{\dagger}$	$0.31^{\dagger}$	0.11	-0.08
LS1	4.564	0.42	1.11	$4.283^{\dagger}$	$0.52^{\dagger}$	$0.37^{\dagger}$	-0.10	-0.02
LS2	2.528	0.62	1.30	$2.151^{\dagger}$	$0.52^{\dagger}$	$0.29^{\dagger}$	0.04	$0.08^{\dagger\dagger\dagger}$
LS3	1.854	0.23	1.34	$1.597^{\dagger}$	$0.36^{\dagger}$	0.07	$0.16^{\dagger\dagger\dagger}$	$0.08^{\dagger\dagger\dagger}$
LS4	1.388	0.37	1.53	$1.210^{\dagger}$	$0.31^{\dagger}$	$0.12^{\dagger\dagger}$	0.03	0.04
LS5	1.067	0.44	1.36	$0.756^{\dagger}$	$0.29^{\dagger}$	$0.21^{\dagger}$	0.10	$0.06^{\dagger\dagger\dagger}$
LS6	0.758	0.50	1.58	$0.457^{\dagger}$	$0.38^{\dagger}$	$0.18^{\dagger}$	0.10	$0.06^{\dagger\dagger\dagger}$
LS7	0.442	0.62	1.43	0.241	$0.34^{\dagger}$	$0.11^{\dagger}$	$0.11^{\dagger\dagger}$	0.00
LS8	0.024	0.73	1.96	$-0.296^{\dagger\dagger\dagger}$	$0.36^{\dagger}$	$0.24^{\dagger}$	0.03	$0.09^{\dagger\dagger\dagger}$
LS9	-0.507	0.69	1.74	$-0.811^{\dagger}$	$0.49^{\dagger}$	$0.21^{\dagger}$	0.05	$0.06^{\dagger\dagger\dagger}$
LS10	-1.973	0.64	1.36	$-2.135^{\dagger}$	$0.56^{\dagger}$	$0.25^{\dagger}$	-0.06	-0.08

Note: Refer to Tables 1 and 2. The regression results are from estimating [1]. DW refers to the Durbin-Watson statistic. †, ††. And ††† indicate statistically significant at the 1%, 5% and 10% levels, respectively.

Table 4: Return Persistence Multi-Index Regression

Decile	Mean Return(%)	$\overline{R}^2$	α	β_1	β_2	β_3	β_4	β_5
EM1	6.187	0.34	4.615†	0.86†	0.13	-0.29	0.20	0.27†
EM2	3.774	0.43	2.570†	0.81†	0.06	0.04	0.07	0.29†
EM3	2.867	0.53	2.102†	0.86†	-0.08	0.08	0.12†††	0.27†
EM4	2.349	0.48	1.792†	0.60†	0.05	-0.09	0.05	0.26†
EM5	1.802	0.59	1.399†	0.66†	0.08	0.01	0.04	0.22†
EM6	1.308	0.53	1.102†	0.52†	0.11	-0.01	0.04	0.09
EM7	0.849	0.44	0.560	0.47†	-0.04	0.01	0.04	0.28†
EM8	0.425	0.61	0.244	0.43†	0.17†	-0.01	0.04	0.19††
EM9	-0.199	0.64	-0.130	0.50†	0.07	-0.11	-0.01	0.18††
EM10	-1.693	0.61	-1.398†	0.57†	0.21†	-0.02	-0.06	0.22†
LS1	4.564	0.53	2.816†	0.46†	0.29††	-0.20	-0.03	0.35†
LS2	2.528	0.66	1.596†	0.49†	0.27†	0.00	0.07†††	0.23†
LS3	1.854	0.36	0.925†	0.38†	0.02	0.16††	0.08††	0.38†
LS4	1.388	0.42	0.880†	0.30†	0.11†	0.02	0.05	0.24††
LS5	1.067	0.51	0.498†	0.27†	0.20†	0.08†††	0.06†††	0.26†
LS6	0.758	0.57	0.243†	0.38†	0.16†	0.10†††	0.06†††	0.25†
LS7	0.442	0.65	0.181†	0.33†	0.09††	0.08	0.01	0.20†
LS8	0.024	0.74	-0.263	0.35†	0.23†	0.01	0.09†	0.12††
LS9	-0.507	0.71	-0.733	0.47†	0.22†	0.03	0.06††	0.15††
LS10	-1.973	0.65	-1.869†	0.54†	0.23†	-0.11	-0.07	0.09

Note: Refer to Tables 1 and 3. . The regression results are from estimating [2]. †, ††. And ††† indicate statistically significant at the 1%, 5% and 10% levels, respectively.

Table 5: Higher Order Moments Regression

Decile	Mean Return(%)	$\bar{R}^2$	α^*	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	$\hat{\eta}$
EM1	6.187	0.75	4.293†	0.67†	0.21	-0.11	0.04	0.19†	0.002†	-0.016††	0.72
EM2	3.774	0.82	3.256†	0.71†	0.15	0.10	-0.02	0.23†	0.012†	-0.034††	0.82
EM3	2.867	0.87	2.446†	0.80†	-0.02	0.13	0.12†	0.24†	0.025†	-0.053†	0.54
EM4	2.349	0.77	2.161†	0.48†	0.10	-0.08	-0.04	0.17†	0.014†	-0.058†	0.88
EM5	1.802	0.86	1.572†	0.59†	0.09	0.01	0.03	0.17†	0.029†	-0.063†††	0.48
EM6	1.308	0.78	0.978†	0.49†	0.10	0.01	0.02	0.11†	0.020†	-0.108††	0.62
EM7	0.849	0.79	1.001	0.47†	-0.06	0.05	0.03	0.25†	0.022†	-0.024	0.92
EM8	0.425	0.84	0.583	0.39†	0.18†	0.04	0.01	0.23†	0.034†	-0.043†††	0.94
EM9	-0.199	0.88	0.808	0.47†	0.07	-0.10	-0.01	0.23†	0.051†	0.043	0.84
EM10	-1.693	0.90	-0.474†	0.48†	0.22†	-0.05	-0.07†	0.31†	0.038†	-0.031	0.82
LS1	4.564	0.84	2.781†	0.42†	0.35†	-0.12	-0.06	0.34†	0.015†	-0.050††	0.64
LS2	2.528	0.88	1.805†	0.49†	0.34†	0.07	0.08†	0.22†	0.035†	0.005	0.88
LS3	1.854	0.78	1.235†	0.34†	0.03	0.22†	0.05††	0.28†	0.034†	-0.056	0.76
LS4	1.388	0.75	0.847†	0.29†	0.11†	0.08	0.03	0.25†	0.025†	-0.047	0.68
LS5	1.067	0.77	0.681†	0.27†	0.20†	0.11†	0.06†	0.26†	0.046†	-0.057	0.82
LS6	0.758	0.86	0.285†	0.36†	0.17†	0.17†	0.04††	0.17†	0.047†	-0.125††	0.56
LS7	0.442	0.88	0.567†	0.30†	0.10†	0.09†	-0.01	0.13†	0.143†	-0.140††	0.62
LS8	0.024	0.90	0.144	0.33†	0.21†	-0.04	0.12†	0.11†	0.091†	-0.114†	0.92
LS9	-0.507	0.93	0.053	0.48†	0.18†	0.04	0.07†	0.15†	0.095†	0.026	0.96
LS10	-1.973	0.87	-1.064†	0.60†	0.24†	-0.16†	-0.04	0.10†	0.023†	0.002	0.82

Note: Refer to Tables 1 and 4. The regression results are from estimating [7] for the multi-period model defined by [2]. The efficiency ratio is given by $\hat{\eta}$. The parameter γ_1 is the weighting associated with the kurtosis factor and γ_2 is the weighting associated with the skew factor. †, ††. And ††† indicate statistically significant at the 1%, 5% and 10% levels, respectively.

Table 6: Ranking of Emerging Market Funds

	Fund No.	RALS Rank	OLS Rank	RALS $\overline{R}^2$	OLS $\overline{R}^2$	RALS α^*	OLS α
Top Performing Funds	EM72	1	7	0.78	0.07	$4.28^{\dagger}$	$3.99^{\dagger}$
	EM79	2	3	0.62	0.17	$3.71^{\dagger}$	$4.33^{\dagger}$
	EM73	3	1	0.56	0.05	$3.26^{\dagger\dagger}$	$5.54^{\dagger}$
	EM61	4	18	0.88	0.53	$3.03^{\dagger}$	$2.44^{\dagger}$
	EM51	5	41	0.66	0.11	$2.91^{\dagger}$	1.46
	EM67	6	19	0.71	0.21	$2.87^{\dagger}$	$2.40^{\dagger}$
	EM37	7	8	0.62	0.23	$2.74^{\dagger}$	$3.97^{\dagger}$
	EM78	8	5	0.48	0.02	$2.72^{\dagger\dagger}$	$4.15^{\dagger\dagger}$
	EM54	9	12	0.70	0.26	$2.66^{\dagger}$	$3.37^{\dagger}$
	EM02	10	13	0.68	0.18	$2.62^{\dagger\dagger\dagger}$	$3.33^{\dagger\dagger\dagger}$
	EM53	11	6	0.70	0.20	$2.61^{\dagger\dagger}$	$4.15^{\dagger}$
	EM39	12	16	0.58	0.09	$2.50^{\dagger}$	$2.67^{\dagger}$
	EM36	13	9	0.64	0.28	$2.45^{\dagger\dagger}$	$3.72^{\dagger}$
	EM92	14	4	0.65	0.09	$2.45^{\dagger\dagger}$	$4.30^{\dagger}$
	EM44	15	60	0.90	0.61	$2.41^{\dagger}$	$1.03^{\dagger\dagger}$
Worst Performing Funds	EM57	92	64	0.68	0.36	-0.21	0.96
	EM74	93	11	0.77	0.02	-0.40	3.56
	EM58	94	81	0.71	0.40	-0.41	0.59
	EM34	95	94	0.66	0.20	-0.46	0.10
	EM84	96	96	0.56	0.00	$-0.93^{\dagger\dagger\dagger}$	$-1.23^{\dagger\dagger\dagger}$

Note: Refer to Tables 1 and 2. The results are from estimating the single factor CAPM: $\overline{R}_{jt} = \alpha_j + \beta_j \overline{R}_{mt} + u_{jt}$ using ordinary least squares and residual augmented least squares. †, ††. And ††† indicate statistically significant at the 1%, 5% and 10% levels, respectively.

Table 7: Ranking of Long/Short Equity Funds

	Fund No.	RALS Rank	CAPM Rank	RALS $\overline{R}^2$	CAPM $\overline{R}^2$	RALS α^*	CAPM α
Top Performing Funds	LS108	1	1	0.80	0.17	$2.99^{\dagger\dagger}$	$5.04^{\dagger\dagger}$
	LS086	2	9	0.75	0.04	$2.77^{\dagger}$	$1.93^{\dagger}$
	LS054	3	19	0.76	0.31	$2.04^{\dagger}$	$1.65^{\dagger}$
	LS034	4	135	0.87	0.49	$2.02^{\dagger}$	0.38
	LS045	5	20	0.78	0.37	$1.89^{\dagger}$	$1.64^{\dagger\dagger\dagger}$
	LS057	6	3	0.66	0.05	$1.83^{\dagger\dagger\dagger}$	$3.47^{\dagger}$
	LS069	7	25	0.76	0.19	$1.83^{\dagger}$	$1.54^{\dagger}$
	LS014	8	41	0.65	0.00	$1.74^{\dagger}$	$1.20^{\dagger}$
	LS099	9	30	0.78	0.33	$1.70^{\dagger}$	$1.39^{\dagger}$
	LS065	10	7	0.78	0.36	$1.69^{\dagger}$	$2.14^{\dagger}$
	LS068	11	5	0.73	0.30	$1.68^{\dagger}$	$2.67^{\dagger}$
	LS066	12	22	0.77	0.12	$1.66^{\dagger}$	$1.62^{\dagger}$
	LS145	13	6	0.59	0.10	$1.65^{\dagger}$	$2.19^{\dagger}$
	LS144	14	129	0.75	0.24	$1.62^{\dagger}$	0.42
	LS096	15	12	0.60	0.05	$1.60^{\dagger}$	$1.78^{\dagger}$
Worst Performing Funds	LS121	153	149	0.70	0.13	-0.34	0.05
	LS078	154	99	0.69	0.26	-0.66	0.67
	LS043	155	150	0.76	0.44	$-0.81^{\dagger\dagger\dagger}$	-0.05
	LS116	156	2	0.84	0.06	-0.87	$3.87^{\dagger\dagger}$
	LS122	157	157	0.62	0.11	$-4.12^{\dagger}$	-0.49

Note: Refer to Tables 1 and 2.. The results are from estimating the single factor CAPM: $\overline{R}_{jt} = \alpha_j + \beta_j \overline{R}_{mt} + u_{jt}$ using ordinary least squares and residual augmented least squares †, ††. And ††† indicate statistically significant at the 1%, 5% and 10% levels, respectively.

[1] Liang (1999) reported estimated hedge fund assets of $190 billion in 1997 based on Hedge Fund Research Inc. (HFR). By 2001, HFR research suggested that the assets were close to $400 billion.

[2] Research by ABP Investments shows that more than 50 percent of all returns on databases are backfilled. Furthermore funds on average have longer track records than direct reporting records. They assessed backfill bias at about 4 percent of annual return, enough to produce a clear influence performance estimates.

[3] Data available from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] The Durbin-Watson statistic indicates the presence of first order serial autocorrelation in single and multi-index regressions as shown in Tables 2 and 3. When the lagged dependent variable is added to the regression, there is no evidence of serial correlation based on either the Durbin-h test or the Ljung-Box statistic at a 1% level of significance. These results are not reported but are available on request from the author(s).

[5] The individual regression results for the 96 and 157 EM and LS funds, respectively, are available from the author, on request.