Lancaster University Management School
Working Paper
2004/050

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An Empirical Investigation of UK Option Returns: Overpricing and the Role of Higher Systematic Moments

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Practical Applications

Options are risky assets and therefore under standard asset pricing theory they should earn a return commensurate with their systematic risk. While many papers examine the empirical performance of various option pricing models few have addressed the issue of option returns. This paper examines the returns on European-style exercise (ESX) equity index option data from the London International Financial Futures and Options Exchange (LIFFE). It is found that there appears to be a significant degree of overpricing on both put and call ESX contracts. Furthermore, the role of higher moments in explaining the return-generating process for these options is explored.

Abstract

The Capital Asset Pricing Model (CAPM) assumes either that all asset returns are normally distributed or that investors have mean-variance preferences. Given empirical observations of asset returns, which document evidence of skewness and kurtosis, both assumptions are suspect. While several studies have investigated incorporating higher moments into asset pricing models using equity data, literature on the contribution of the third and fourth moments in explaining the return-generating process in options markets is sparse. Using a two-pass methodology we investigate an asset pricing model that allows moments of higher order than two using European-style exercise (ESX) equity index option data from the London International Financial Futures and Options Exchange (LIFFE). Our empirical investigation shows that ESX option contracts appear to be overpriced and that on average almost all puts and calls earn negative daily returns during our ten-year sample period. Furthermore, our regression results show that systematic variance has a significant role in explaining the cross-section of option returns and that the role of systematic skewness and systematic kurtosis throughout the sample period is less clear.

Keywords: option returns; CAPM; systematic; skewness; kurtosis; comoments; cross-section

INTRODUCTION

The fundamental assertion that the capital asset pricing model (CAPM) makes is that investors in a mean-variance world only price market risk. This has been questioned almost from the inception of the model and indeed there is a body of literature that identifies a number of non-market risk factors that appear to be priced. In particular, Fama and French[1] find that the non-market risk factors size and book-to-market value are statistically significant in explaining the cross-section of equity returns. Interestingly, from the perspective of this study, Chung, Johnson and Schill[2] suggest that these non-market risk factors are in fact proxies for omitted higher moments of asset return distributions.

In a CAPM world investors only care about mean and variance for portfolio returns and covariance for individual asset returns. However, it is well documented in the literature that unconditional asset return distributions are not normal and the mean and variance of returns alone are insufficient to characterise the return distribution completely.[3] In particular, the probability of extreme returns that are observed empirically is greater than the probability of extreme returns under the normal distribution, i.e., empirical distributions are leptokurtotic. These observations have led researchers to investigate the third moment – skewness – and the fourth moment – kurtosis – in an effort to explain the cross-section of asset returns. More specifically investigations into higher moment CAPM models have examined the role of systematic skewness, which is the ratio given by the coskewness of an asset return to market skewness, and systematic kurtosis, which is the ratio given by the cokurtosis of an asset return to market kurtosis.

The purpose of this paper is twofold. Firstly, London International Financial Futures and Options Exchange (LIFFE) European-style exercise (ESX) index option returns are calculated on a daily basis and examined in risk-return space. Secondly, we investigate the CAPM incorporating systematic moments of higher order than two using options data and we assess whether or not these higher order systematic moment risks might be priced. Using index options data provides an exceptional opportunity to test the extended CAPM model due to the absence of idiosyncratic risk and the nonlinear nature of option payoffs.

The paper is organized as follows. The next section examines the CAPM literature relating to the inclusion of moments of higher order than two. The following sections examine investor preferences for higher moments, the empirical form of the expanded CAPM model, the data used in the study and the method used to calculate option returns, and the empirical findings of the study. The final section contains a summary discussion and concludes the paper.

EMPIRICAL TESTS OF THE CAPM INCORPORATING HIGHER SYSTEMATIC MOMENTS

Sharpe,[4] Lintner[5] and Mossin[6] developed the first formulations of the mean-variance capital asset pricing model (CAPM). Early tests of the model were generally supportive (e.g., Black, Jensen and Scholes;[7] Fama and MacBeth[8]) although there were inconsistencies reported with respect to the slope of the regression line and the intercept term. Banz,[9] however, challenged the validity of the CAPM by showing that firm size explains the cross-sectional variation in average returns better than the CAPM beta. Fama and French[1] show that the size effect may be so significant that it questions the validity of the CAPM in any economically meaningful sense. Furthermore, when they include the ratio of the book value of a firm's common equity to its market value as an explanatory variable in addition to size, they find this so-called value factor is also significant in explaining the cross-sectional variation in returns.

The findings of Fama and French[1] have themselves come under close scrutiny, particularly in relation to their claims that the CAPM beta has no role in explaining cross-sectional variation in returns. Kothari, Shanken and Sloan[10] argue that the findings depend critically on the interpretation of the statistical results in their study. In particular, Fama and French's estimates for the coefficient on beta have high standard errors and are possibly too noisy to invalidate the CAPM.[11] Setting aside these criticisms the general reaction to the Fama and French insights has been for researchers to focus on alternative asset pricing models to the original CAPM.

Equity Markets Tests

Kraus and Litzenberger[12] extend the traditional CAPM to include the effect of systematic skewness on asset pricing and choose to ignore terms of the fourth and higher order on the basis that "aversion to standard deviation and preference for positive skewness are general characteristics of all investors having utility functions displaying the desirable behaviouristic attributes of decreasing marginal utility of wealth and non-increasing absolute risk aversion" whereas general investor attitudes towards higher moments such as kurtosis are not easily determined. The results of their empirical study of equity data support a three moment pricing model. Further they find that investors are averse to variance and prefer positive skewness.

Friend and Westerfield[13] offer what they term a "more comprehensive" testing of the Kraus and Litzenberger[12] hypothesis. They incorporate bonds into the analysis by including them in the market portfolio as well as stocks and conclude that the Kraus-Litzenberger attempt to incorporate systematic skewness into the pricing model is not successful and that the significance of skewness within the pricing model is particularly sensitive to the choice of market proxy.

Whereas Kraus and Litzenberger[12] and Friend and Westerfield[13] use similar forms of a two-pass regression methodology, Lim[14] tests a three-moment CAPM using Hansen's[15] generalised method of moments (GMM) allowing a proper treatment of nonnormal data. Another primary advantage of this technique is that it avoids the problem of errors-in-variables, a nontrivial problem associated with the two-pass methodology.[16] Lim,[14] using similar data to Kraus and Litzenberger,[12] finds significant evidence in support of including a skewness parameter into the asset-pricing model.

Fang and Lai[17] extend the CAPM framework further in examining the impact of kurtosis. They derive and empirically test a four-moment asset pricing model in which systematic kurtosis, in addition to systematic variance and systematic skewness, contributes to the risk premium of an asset. Employing an instrumental variable estimation the model is tested using equity data. Their results show that, in the presence of skewness and kurtosis, the expected excess rate of return is related not only to systematic variance but also to systematic skewness and systematic kurtosis.

Dittmar[18] argues that the inclusion of the fourth moment in the asset-pricing model is justified as a necessary condition for standard risk aversion is decreasing absolute prudence and he theoretically links such preferences to an aversion for kurtosis. Like Fang and Lai,[17] Dittmar[18] concludes that the four-moment CAPM prices the cross-section of returns much more effectively that the traditional CAPM and that it outperforms multifactor models.

Harvey and Siddique[19] initially test the traditional CAPM single factor asset-pricing model and conclude that systematic risk as measured by beta fails to explain expected excess returns. They suggest that a possible explanation for this is that if investors are aware of skewness in asset price returns the expected excess returns should include a component attributable to conditional coskewness. Tests on a pricing model incorporating systematic skewness show that this higher moment is indeed significant in explaining expected excess returns.

Future and Option Markets Tests

Christie-David and Chaudhry[20] investigate the contribution of the third and fourth moments in explaining the return-generating process in futures markets. Empirical tests of their four-moment model show that the second, third and fourth systematic moments are all important in explaining futures returns. Furthermore, their results are robust to the use of several different market proxies. From a financial options perspective there appears to be a scarcity of empirical investigations into the validity of the CAPM and extensions thereof using options market data.

THE PRICING OF HIGHER MOMENTS

It is common in financial modelling to assume that the distribution of asset returns is normally distributed thereby allowing mean-variance analysis. In this framework it is assumed that investors are not concerned about moments of higher order than the variance. However, Levy[21] suggests that higher moments should be included in asset pricing models even if they only marginally contribute to describing the return distribution. This may explain why the CAPM has performed relatively poorly in empirical tests.

Given the empirical observations of skewed and fat tailed asset pricing distributions it should follow that investors have preferences about higher moments. Scott and Horvath[22] show that the preference direction is positive (negative) for positive (negative) values of every odd central moment and negative for every even central moment. In other words, investors will have positive preference for skewness and dislike kurtosis.

Chung et al[2] argue that there is no reason to stop with the fourth moment as we are in this study. After all they point out that investors are concerned with the risk of ruin, for example, and they note that the popularity of lottery type games shows that the right hand tail of return distributions is also important from an investor's perspective. Dittmar,[18] however, argues that moments beyond the fourth are difficult to interpret intuitively and are not explicitly restricted by standard preference theory. In any case, although not theoretically supported, the extension of this study to include moments of higher order than four would be trivial.

METHODOLOGY

In principle, to test an asset-pricing model like the CAPM one would regress asset or portfolio returns on their betas. However, Dimson and Mussavian[23] point out that beta is not known and can only be estimated with error and this violates the assumptions underpinning regression. The two-pass methodology developed by Black, Jensen and Scholes[7] and Fama and MacBeth[8] overcomes this problem by firstly estimating the beta of each asset with respect to a factor in a time-series regression, and secondly using the estimated betas in a cross-sectional regression to estimate the risk premium of the factor. Kan and Zhang[24] note that then the primary question of interest is whether the estimated risk premium associated with a given factor is significantly different from zero, i.e., is the beta risk of a particular factor priced.

A four-moment asset pricing models is outlined below where the term on the left-hand side is the expected realised excess return[25] on asset j and the variables β, γ, and δ, on the right-hand side represent measures of systematic variance, systematic skewness and systematic kurtosis respectively.

$$E(R_j) = a_0 + a_1\tilde{\beta}_j + a_2\tilde{\gamma}_j + a_3\tilde{\delta}_j$$

where

$$\tilde{\beta}_j = \left[\sum_t \left(\tilde{R}_{jt} - \bar{R}_{jt}\right)\left(\tilde{R}_{mt} - \bar{R}_{mt}\right)\right] / \sum_t \left[\left(\tilde{R}_{mt} - \bar{R}_{mt}\right)^2\right]$$
$$\tilde{\gamma}_j = \left[\sum_t \left(\tilde{R}_{jt} - \bar{R}_{jt}\right)\left(\tilde{R}_{mt} - \bar{R}_{mt}\right)^2\right] / \sum_t \left[\left(\tilde{R}_{mt} - \bar{R}_{mt}\right)^3\right]$$
$$\tilde{\delta}_j = \left[\sum_t \left(\tilde{R}_{jt} - \bar{R}_{jt}\right)\left(\tilde{R}_{mt} - \bar{R}_{mt}\right)^3\right] / \sum_t \left[\left(\tilde{R}_{mt} - \bar{R}_{mt}\right)^4\right]$$

and

$\tilde{R}_{jt}$ is the return on asset *j* at time *t*.

$\bar{R}_{jt}$ is the expected return on asset *j* at time *t*.

$\tilde{R}_{mt}$ is the return on the *market* at time *t*.

$\bar{R}_{mt}$ is the expected return on the *market* at time *t*.

Since options data is being used in the study, option bins need to be created in order to have consistent time-series observations of option returns. Option bins are classified according to an option's delta[26] and range from -0.15 to -0.90 for puts and from +0.15 to +0.90 for calls with intervals of 0.15. The delta is the rate of change of the Black-Scholes pricing function with respect to the underlying asset. It gives us the change in the value of an option induced by a unit change in the underlying asset's spot value. The adjusted Black-Scholes model[27] used to calculate the delta measure for calls and puts is outlined below.

$$c = e^{-r\tau}[FN(d_1) - KN(d_2)]$$
$$p = e^{-r\tau}[KN(-d_2) - FN(-d_1)]$$

$$d_1 = \frac{\ln(F/K) + \sigma^2\tau/2}{\sigma\sqrt{\tau}}$$
$$d_2 = \frac{\ln(F/K) - \sigma^2\tau/2}{\sigma\sqrt{\tau}} = d_1 - \sigma\sqrt{\tau}$$

where

c(p) = call (put) option price

N ( ) = the cumulative standard normal distribution

r = risk-free rate of interest

F = matched maturity futures price

K = strike price

τ = time-to-maturity

σ = volatility[28]

Individual option positions have their own particular delta values. Long call options will have delta values between zero and one. Specifically, out-of-the-money (OTM) call options will have positive values closer to zero while in-the-money (ITM) call options will have positive values closer to one. Long put options on the other hand will have delta values that lie between zero and minus one. ITM put options will have negative values closer to minus one whereas OTM put options' delta values will be negative but closer to zero.

To carry out the empirical investigation a two-pass methodology is employed as follows. On any given day we obtain *rolling estimates* of β, γ, and δ for each option bin[29] using the previously outlined equations (on p.8) and daily data for 120 days prior to the estimation date. These estimates can then be used in daily cross sectional regressions.[30] Results from the daily regressions are then cumulated and tested against priors.

DATA AND CALCULATION OF RETURNS

Data

The data is end-of-day FTSE 100 European style exercise option data obtained from LIFFE through their on-line download service for the ten-year period 1992-2001. There are contracts expiring in March, June, September and December plus the two other additional months such that the four nearest calendar months are always available for trading. The options expire on the third Friday of the month and settlement is in cash on the first business day after the last trading day (which is the same as the exercise day). The interval between exercise prices is either 50 or 100 index points, but the Exchange reserves the right to introduce tighter strike intervals (e.g., 25 points). The data was downloaded in text format and contained the following relevant fields:[31] trade date, option type, expiry date, strike price, closing price, instrument settlement price, volume, volatility and closing bid/offer.

The range of strike prices available throughout the data period is illustrated in Figure 1 and it is apparent that many contracts "available" towards the latter end of the data sample are so far from the money that they will not be actively traded.[32]

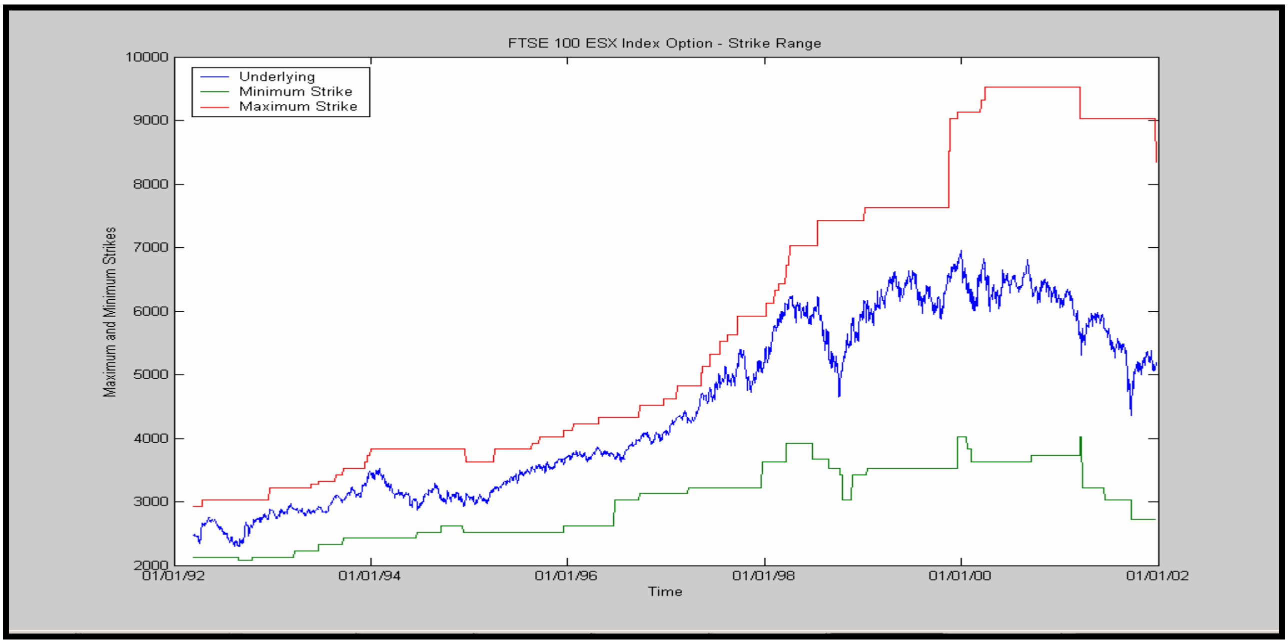

Figure 1: Range of Strike Prices

Option Returns

Options are risky assets and therefore under standard asset pricing theory they should earn a return commensurate with their systematic risk. Coval and Shumway[33] show that options which deliver payoffs in bad states of the world will earn lower returns than those that deliver payoffs in good states. One might interpret this as investors foregoing some level of return for the insurance type protection that certain put option positions offer.[34] The calculation of option returns is not a straightforward task like calculating returns on equities for example as the moneyness characteristic of options contracts changes according to movements in the underlying asset. Therefore, it is necessary to group options into bins based on type, moneyness measure,[35] and time-to-maturity. This process can be carried out in a number of different ways and the following discussion looks at how previous studies of option returns have dealt with this task.

Coval and Shumway[33] in their examination of expected option returns point out that under mild assumptions expected call returns exceed those of the underlying asset whereas expected put returns are below the risk-free rate. Furthermore, they also note that the expected returns on puts and calls are increasing in the strike price (for US Data). The method they employ to calculate index option returns is based on the first bid-ask quote after 9 a.m. Central Standard Time (CST), so as such uses opening prices as opposed to closing prices. They take options that are to expire during the following calendar month, which results in options with times-to-expiration of roughly between 20 and 50 days. When calculating option returns they use the midpoint of the bid-ask spread. Options are classified into five groups according to their strike prices relative to the level of the underlying index. This ensures that exactly one option exists within each group at each point in time although the moneyness of each bin changes over time. The returns reported in Coval and Shumway[33] are arithmetic returns.[36]

For the CBOE, Sheikh and Ronn[37] limit their attention to the thirty most actively traded individual equity options to examine patterns of returns. Within this option class they focus daily on the nearest the money, shortest maturity options (but with at least eight days to maturity) with a bid price of at least $1.00. These criteria are imposed to ensure that the most liquid options are examined. On a given day, for each option class, they find the option that satisfies their criteria and take the last bid-ask quote for the option on that day and the subsequent day and use the average of the bid and ask prices to compute the option return. The returns reported are logarithmic returns.

Jones[38] examines the possibility that multiple sources of priced risk appear necessary to explain the expected returns of equity index options. Using S&P 500 index options data and factor analysis he attempts to identify the sources of the priced risk. Option returns are calculated based on holding an option from the close of one trading day to the close of the next trading day. Only options with at least ten days to expiration are considered. Following Coval and Shumway[33] arithmetic returns are calculated using the average of the bid-ask spread.

In our study, option returns are calculated using daily end-of-day data. On every trade date we identify what we term the *first nearby*[39] and *second nearby*[40] option contracts as these contracts are the most actively traded contracts on LIFFE. Puts and calls are classified into 5 bins according to a delta-space measure previously outlined. When calculating option returns we use the closing price[41] as reported in the LIFFE data. Option returns are calculated based on holding an option from the close of one trading day to the close of the next trading day. Throughout this paper we report arithmetic returns in decimal format and only examine trade days where observations exist for all bins under consideration, e.g., first nearby contract bins, second nearby contract bins, etc.

EMPIRICAL RESULTS

The Underlying Asset

LIFFE prices the FTSE 100 stock index option as if it was an option on a matched maturity futures contract, hence the term Instrument Settlement Price for the quoted matched maturity futures price. To this end, LIFFE provides matched maturity futures price information with its option price data. However, since there are only four FTSE 100 futures contracts traded on LIFFE (March, June, September, and December) a true matched maturity futures price for a given option may not exist. The exchange, however, provides an implied futures price and since, in practice, only the near-dated futures contract trades heavily[42] this is the contract used to calculate that implied price. This is achieved by adjusting the near-dated, or front-end, futures price using a cost of carry calculation. Information relevant to this calculation, most importantly, a consensus ex-ante assessment of the dividend yield on the index portfolio, is provided by market traders.

Given that we are interested in the covariance, coskewness, and cokurtosis of option returns with the market index it is necessary to examine the characteristics of the FTSE 100 index. Accordingly, summary statistics including mean, variance, skewness and kurtosis estimates are reported in Table 1. Furthermore, the results of skewness, excess kurtosis and Jarque-Bera normality tests are reported.

For the FTSE100 index annual mean returns over each of the ten-year period are generally positive with only three years showing negative returns. Negative skewness is prevalent for most years but is generally insignificant. In general there is excess positive kurtosis in the distributions with it being significant in five of the sample years. The Jarque-Bera test for normality rejects normality in half of the years examined. It is clear therefore that over the entire period there is, albeit weak, evidence of skewness in the underlying asset returns. More significantly there is strong statistically significant evidence of excess kurtosis in the underlying asset return distribution over the sample period and that this is the key driver of the nonnormality exhibited.

[INSERT TABLE 1 ABOUT HERE]

The returns and distribution of returns for the FTSE 100 index over the sample period are illustrated in Figure 2. An interesting observation is the increased level of volatility in the index returns post 1998.

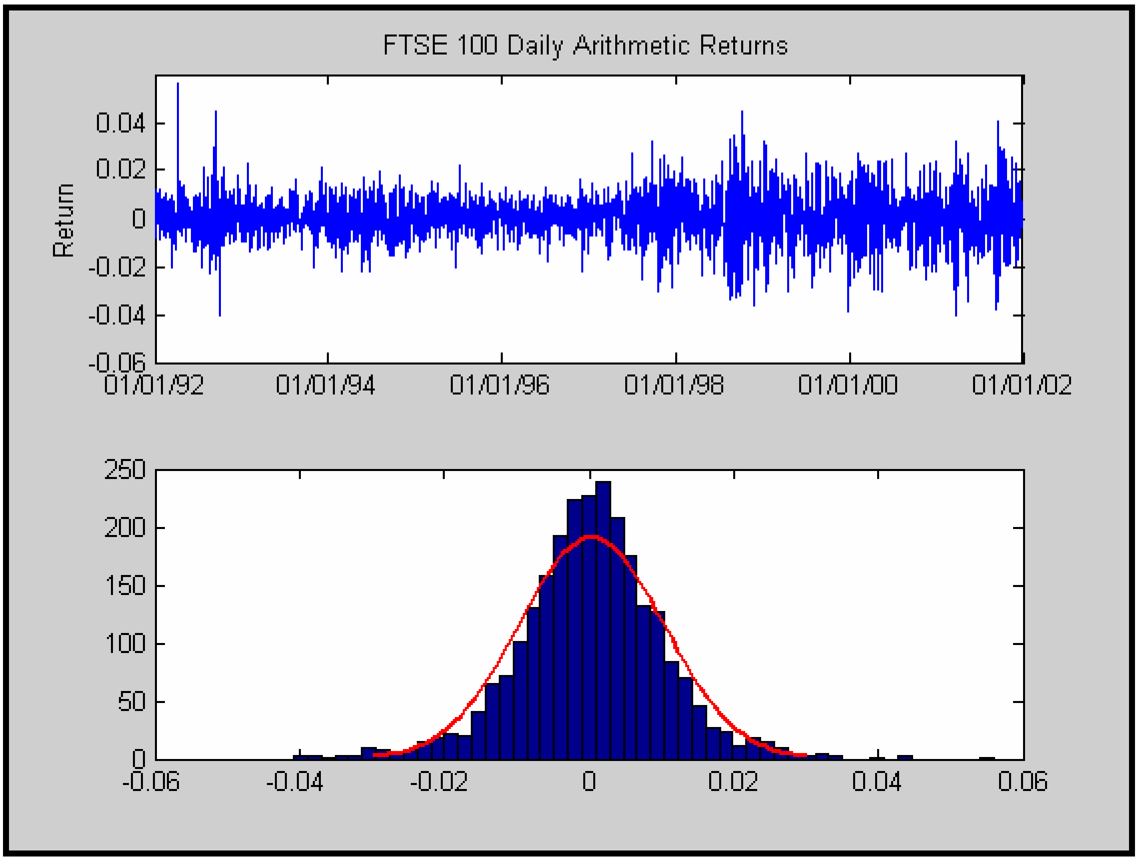

Figure 2: FTSE 100 Daily Arithmetic Returns 1992-2001

FTSE 100 ESX Equity Index Option Returns

Options, just like all other assets, should earn returns commensurate with their risk. Coval and Shumway[33] state "in a Black-Scholes/CAPM asset-pricing framework, call options always have betas that are larger in absolute value than the assets upon which they are written." The opposite should be true for put options, which offer protective insurance to the option holder and will therefore have negative betas. This theoretical perspective is illustrated in Figure 3.

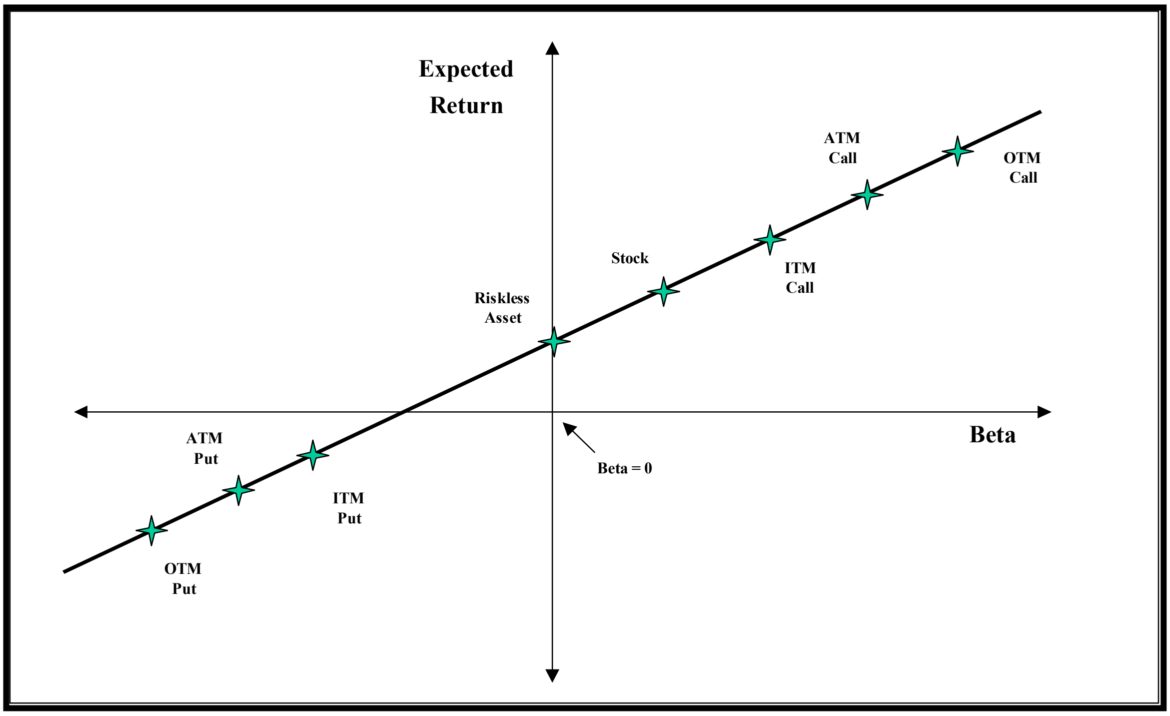

Figure 3: Options and the Security Market Line

Table 2 contains summary statistics for all option bins constructed using the previously defined delta space measure. As alluded to previously, call options with deltas of between 0.15 and 0.90 are divided into five equally spaced bins while put options with deltas of between -0.15 and -0.90 are similarly treated. Only days where observations for all bins existed are included in our analysis. In general, option bins are characterised by negative daily returns (even for call option bins which we would expect to have positive returns on average) and significant nonnormality. The returns on second nearby option bins are higher than their first nearby counterparts. The option bins are quite positively skewed compared to the underlying, which only exhibits marginal positive skewness. All of the option bins have kurtosis figures in excess of the Normal benchmark of three. Volume figures show that the most heavily traded options are those at-the-money and out-of-the-money.

[INSERT TABLE 2 ABOUT HERE]

Table 3 presents average systematic moment statistics for all option bins.[43] Three measures of systematic variance are presented: a time-series estimate of beta, a Black-Scholes beta and a money-weighted beta estimated from a regression of absolute changes in option value on absolute changes in the level of the underlying. The systematic variance (beta) figures (calculated using the previously defined equations on p.8) in particular are of interest and they conform to expectations from our illustration of expected option positions on the security market line earlier, i.e., monotonically *increasing* in strike price. They are consistent with the estimated Black-Scholes betas also. The money-weighted beta estimates are also intuitively appealing. Two measures of systematic kurtosis are presented, the first a time-series estimate and the second what we term an orthogonalised estimate. The equations used in the estimation of our measures of systematic variance and systematic kurtosis are presented as part of the table.

[INSERT TABLE 3 ABOUT HERE]

The behaviour of the systematic variance estimates is interesting in that absolute beta values get smaller post 1997 and get particularly squeezed in 1998 possibly as a result of the Long Term Capital Management crisis. The behaviour of returns around this period along with a volatility index is plotted in Figure 4 and clearly shows volatility spikes towards the end of 1998.

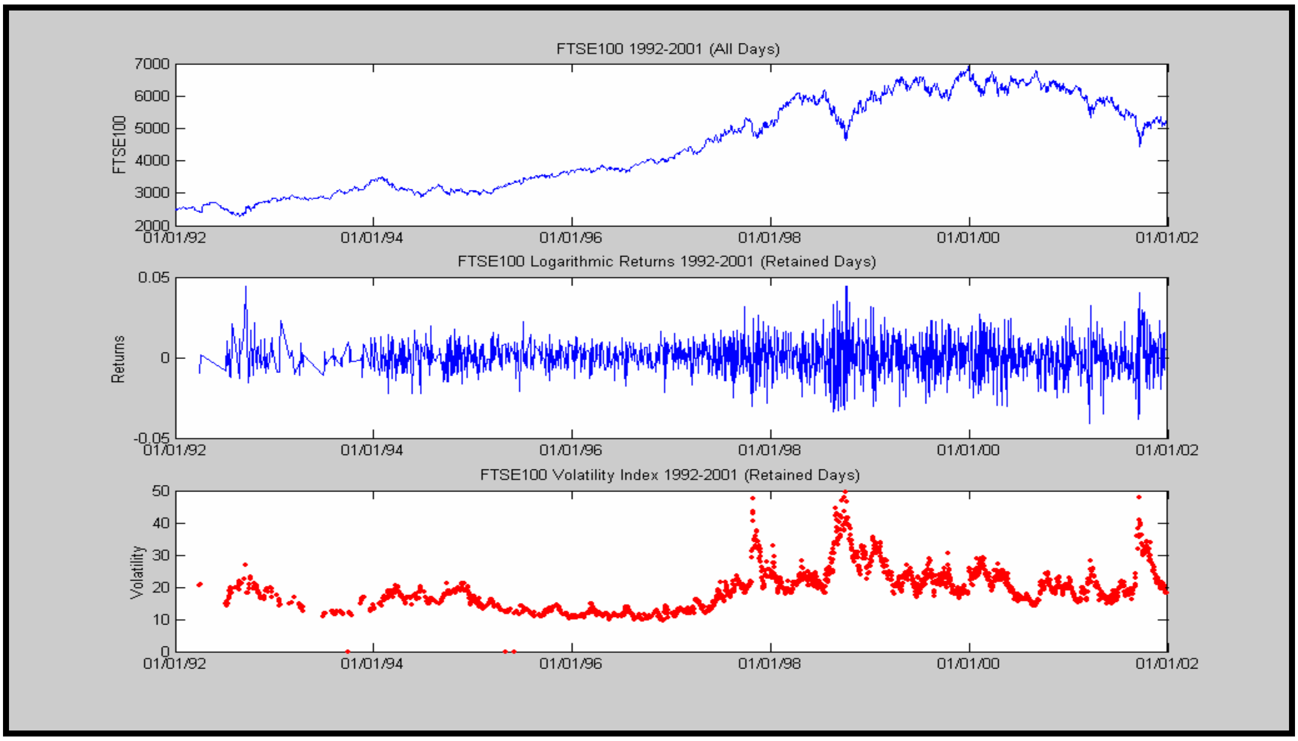

Figure 4: FTSE100 Index: Level, Returns and Volatility Index

Plots of systematic variance, systematic skewness and systematic kurtosis (not orthogonalised) over the sample period are presented in Figure 5 and further illustrate the behaviour of the systematic moments under consideration.

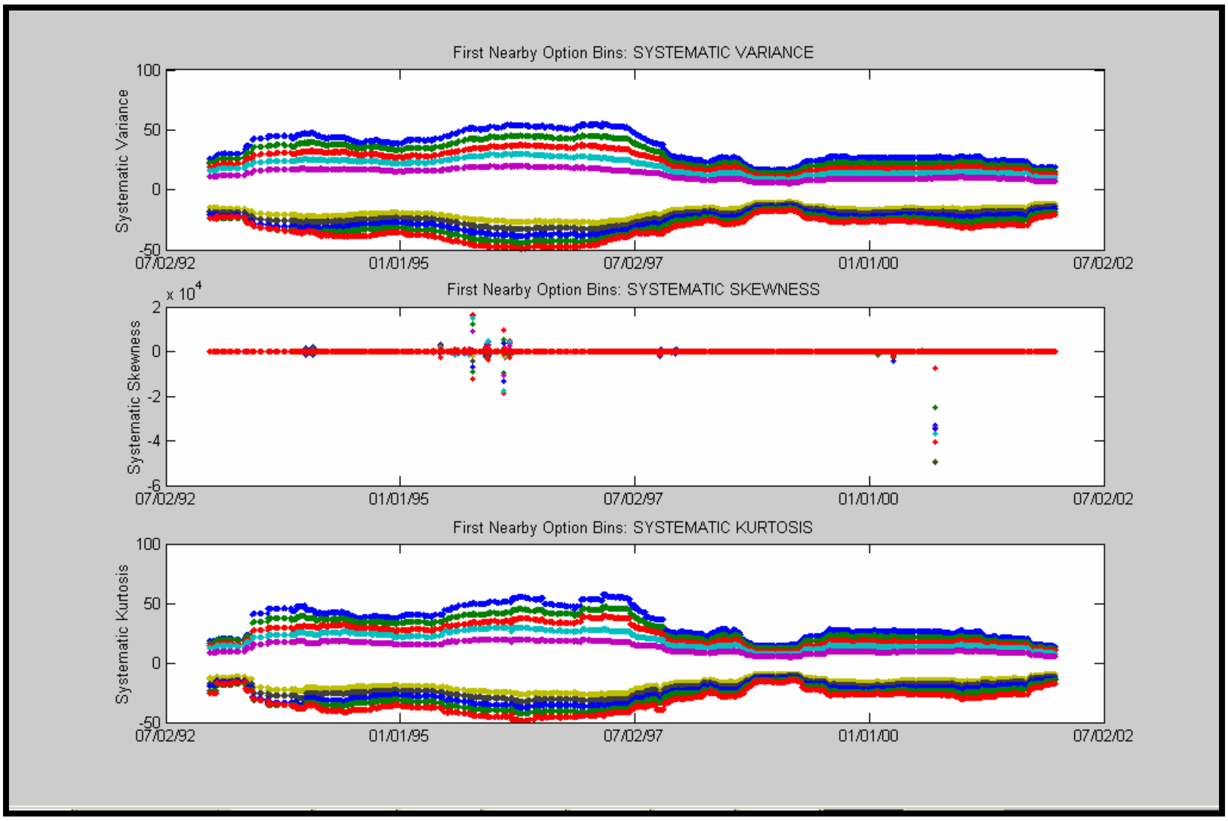

Figure 5: Systematic Moment Plots For First Nearby Option Bins

The middle plot suggests that systematic skewness is badly behaved in that it changes sign; it also tends to have a number of extremely large outliers. The other important point of interest is the similarity between the systematic variance and systematic kurtosis plots. The implications of these observations impact on the regression analysis that we carry out later in the paper.

As a final illustration of the results to date Figure 6 contains a subplot of systematic skewness (with a restricted *y*-axis) to illustrate its behaviour excluding its most extreme observations and a plot of the orthogonalised systematic kurtosis measure presented above as part of Table 3. From these plots one can observe that systematic skewness seems to be intermittently susceptible to periods of unstable behaviour. More importantly by comparing the plot of the orthogonalised systematic kurtosis measure in the figures below with the previously illustrated systematic variance and systematic kurtosis plots one can see that the orthogonalised systematic kurtosis plot is very different, which is to be expected.

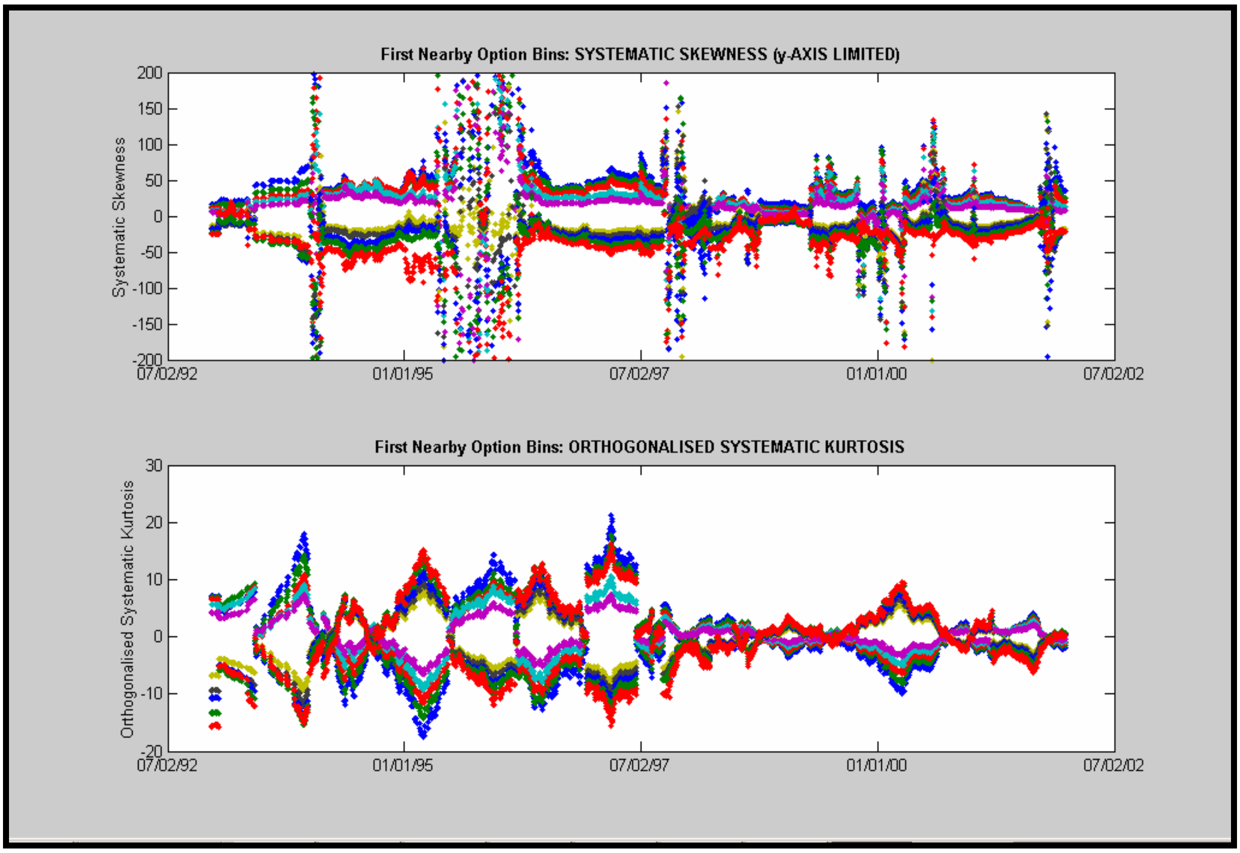

Figure 6: Further Systematic Moment Plots For First Nearby Option Bins

In an attempt to summarise the results of the first part of the empirical investigation into the returns generating process for ESX equity index options we plot a risk-return space representation of option returns below where first and second nearby option bin returns are plotted against corresponding average option bin betas (estimated using the equations presented on p.8). It is clear from Figure 7 below (and Table 2) that average returns on most option bins are negative. The negativity of OTM option returns is particularly evident and it can be seen that first nearby options in general have more negative returns than their second nearby counterparts. The fact that the majority of average call option returns are significantly negative is surprising given our expectation that call returns would on average exceed the return on the underlying asset, which in our sample was on average approximately 0.0003 per day

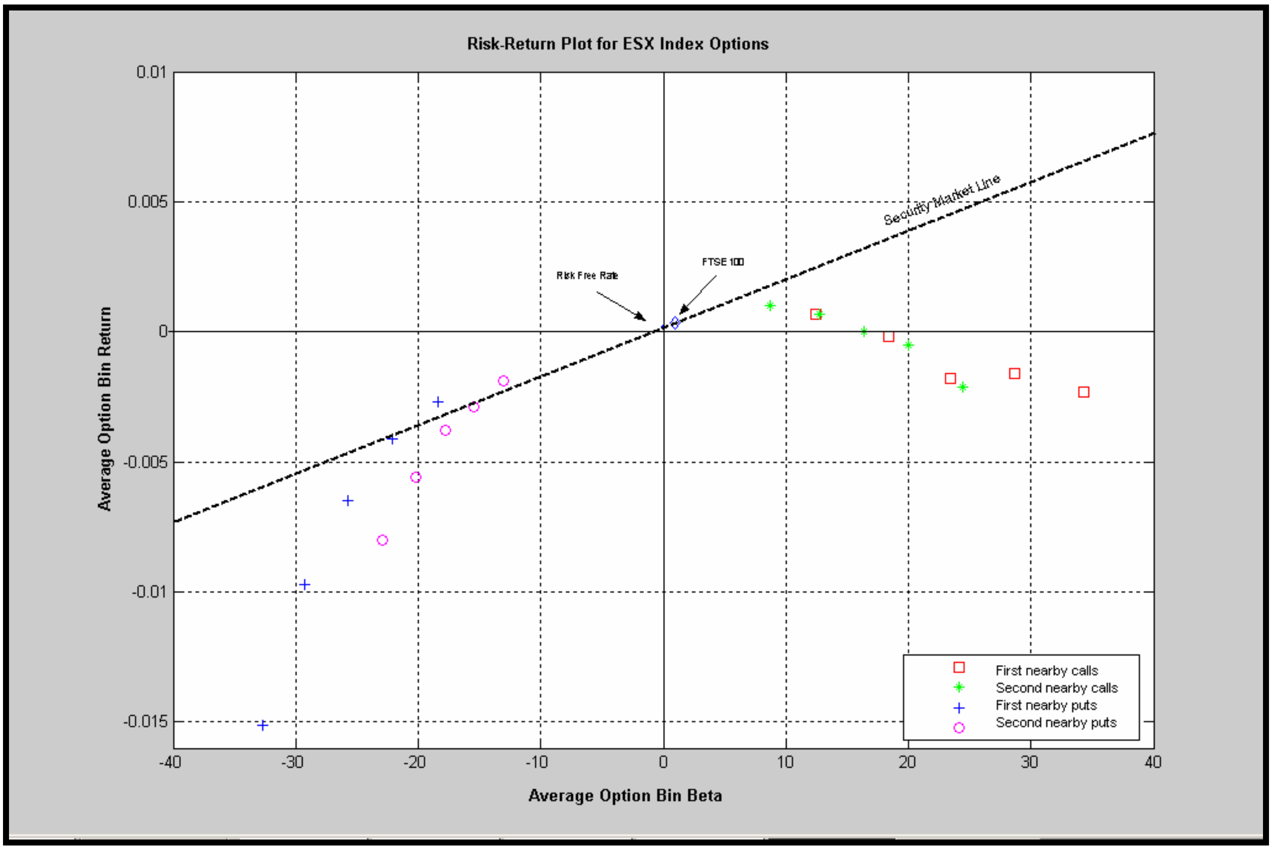

Figure 7: A Risk Return Plot for ESX Equity Index Options

Two Stage Time Series Cross-Section Regressions

Given the results of the empirical investigation to date the two stage time series cross-sectional regressions we can employ are restricted. In particular, due to lack of stability in the systematic skewness parameter we will not include it in our regression analysis. This limitation is mitigated to a certain extent by the fact that kurtosis seems to be the dominant cause of nonnormality in the market index. Therefore we run regressions using only systematic variance and (orthogonalised) systematic kurtosis estimates in an investigation of how well an extended CAPM works in explaining option returns.

Table 4 contains results of daily cross sectional regressions for all option bins over the sample period. Three models are tested: Model I is the traditional CAPM, Model II is an extended CAPM with a kurtosis term included and Model III regresses option returns on only a kurtosis term. The regressions are run for all options together and for puts and calls separately. Model I results are mixed and contrary to expectations in some cases. When all options are included in the regressions beta is insignificant in explaining option returns (the points on Figure 7 clearly lie off the SML). When only call options are included in the regressions the beta slope coefficient is significantly *negative*. The beta coefficient is positive and significant when only puts are included in the regressions. In all cases for Model I the intercept is significant possibly highlighting another factor that is being priced in the option contract under investigation. The high R^2 figures are to be expected given that the main driver of option returns is the market index. Model II features significant intercept terms for all three regressions run. Systematic variance (beta) is only significant for the regression involving put options. Systematic kurtosis is significant when all options are included in the regressions and when puts are regressed separately. Even though systematic variance was significant for Model I when only calls were used in the regression this is not the case for Model II where the beta coefficient is insignificant. The R^2 figures are marginally higher in all cases for Model II compared to Model I. Model III is characterised by much lower R^2 figures and generally insignificant slope coefficients. The results presented in Table 4 should be interpreted cautiously - the averaging process used to examine the slope coefficients and their significance affects the results for this traditional approach to testing asset pricing models. For example, on downdays the slope coefficient for calls will be negative while on updays it will be positive. Averaging the coefficients will have obvious implications in the significance tests as the positive coefficients and negative coefficients will tend to cancel each other out.

[INSERT TABLE 4 ABOUT HERE]

Pettengill et al[44] account for a conditional relationship between comoments and realised returns. They point out that if the realised market return is above the risk-free return, betas and returns should be positively related, but where the realised market return is below that of the risk-free asset this relationship will be negative. In order to allow for this they divide their dataset into updays, days on which the realised market returns is above the risk-free return, and downdays, days on which the realised market returns are below the risk-free return. In view of this Table 5 contains results of daily cross sectional regressions for all option bins over the sample period where the data has been split into updays and downdays. As is Table 4 three models are presented and regressions are run for calls alone, puts alone, and calls and puts together.

Applying the above procedure has a dramatic effect on the results. The significance of beta is now very clear in all of the regressions run. It is also of correct sign, positive on updays and negative on downdays. The size of the slope coefficients on updays and downdays are also encouraging as they are of a similar magnitude. There are some significant results with respect to the kurtosis term in Model II but the issue of collinearity is a concern given the effect of its inclusion on the significance of the beta coefficient. This concern also affects our interpretation of the Model III results because even though the kurtosis term is significant in some cases when returns are regressed on it alone the R^2 figures are low in comparison to Models I and II.

[INSERT TABLE 5 ABOUT HERE]

Overall, the results of our empirical analysis are variable. The basic CAPM model performs relatively well in explaining the variation in option returns over the sample period. However, we are unable to make strong inferences for a model including systematic skewness (we discard this variable due to its unstable characteristics) and systematic kurtosis (mixed empirical results and collinearity concerns). Most notably, however, the significance of the intercept term throughout the regression analysis highlights the inability of the models presented to explain the return generating process for ESX index options.

SUMMARY DISCUSSION AND CONCLUSION

The purpose of this paper was to carry out an empirical investigation into the returns generating process for LIFFE ESX options over a ten-year sample period. The first contribution of the paper is to provide a risk-return analysis of ESX option contracts. According to classical finance theory, options just like all other assets should earn a return commensurate with their systematic risk as measured by beta. Options theory suggests that call options should on average earn returns greater than that of the asset upon which they are written while put options should earn returns below that of the risk free rate given that investors are willing to pay for their insurance-like properties The empirical results presented in this paper conform with expectations in that call betas exceed that of the underlying and are increasing in strike price whereas put betas are negative and increasing in strike price.

However, the most interesting aspect of the study is in the levels of returns provided by the options examined. Both puts and calls (in almost all cases) exhibit negative daily arithmetic returns on average. This is particularly anomalous with regards to the call returns, which one would expect to have positive returns on average. One conclusion that might be drawn from the analysis is that ESX option contracts are just bad value, i.e., they are overpriced, possibly as a result of the poor liquidity on the LIFFE options exchange. Another factor in this apparent overpricing may be that static buy and hold strategies combined with derivative instruments can achieve the same payoffs as dynamic strategies relying on stocks and bonds. Accordingly, Gibson and Zimmermann[45] note that in order to enhance the full risk-return spectrum, static strategies require diversification and leverage opportunities which is why investors may be willing to pay above the odds for the diversification and leverage opportunities offered by derivative instruments. The overpricing hypothesis would seem to merit further investigation and an interesting addition to the preceding analysis would be to include options with very short times to maturity, i.e., less than 15 days, which were excluded because of our definitions of first and second nearby option contracts.

The second contribution of the paper is to investigate the possibility that systematic moments of higher order than two might explain the returns generated on ESX option contracts. Systematic skewnesses were observed to be unstable over the sample period and were therefore not suitable for use in this study. This resulted in its removal from the analysis. To investigate the *reduced* model (second and fourth moments), cross sectional regressions were run across the 1,610 days for which observations existed for all option bins. The most significant result from the regression analysis is the performance of the traditional single-factor CAPM, in that, while explaining approximately 70-85% of the variation in option returns across the sample period the regression results consistently showed a significant intercept term, suggesting that some other factor(s) may need to be included. The role of systematic kurtosis was less clear (its collinearity with covariance affecting the interpretation of results) and the role of systematic skewness was not empirically tested.

Despite the problems encountered in the regression analysis and the mixed incremental performance of the systematic kurtosis term, the role of the extended CAPM in explaining equity index option returns merits further investigation. Developing a different measure/estimation technique might overcome the problem of a lack of stability in the systematic skewness parameter and the orthogonalisation of the systematic kurtosis term can be further explored. Furthermore, an obvious extension of our analysis would be to employ Hansen's[15] generalised method of moments which is distribution free and avoids the errors in variable problem associated with the traditional two stage time series cross sectional approach employed in this paper.

APPENDIX A

DATA FIELD DESCRIPTIONS		
Trading Date	**Type**	**Expiry**
The date to which the information relates.	Identifier as to whether the option is a call or a put.	The month in which the contract legally expires. ESX options expire on the third Friday of every month.
Strike Price	**Closing Price**	**Instrument Settlement Price (Underlying)**
The price at which the holder of the option can buy or sell the underlying index. The interval between strike prices is either 50 or 100 index points. Additional exercise prices are introduced when the index has exceeded the second highest, or fallen below the second lowest, available exercise price.	Option settlement price is defined as "an average of traded prices in the last 30 seconds of trading; if there is no trading the pit observer asks for bid/offers in the pit and takes the average of these - in this case the contract can settle outside the high/low range."[46]	LIFFE prices the FTSE 100 stock index option as if it was an option on a matched maturity futures contract, hence the term Instrument Settlement Price for the quoted matched maturity futures price. To this end, LIFFE provides matched maturity futures price information with its option price data.
Volume	**Closing Bid/Closing Offer**	
The total number of matched trades on the trading day in question.	The last bid and offer in the marketplace before settlement.	

Table 1: Summary Statistics for Daily Arithmetic Returns Data on the FTSE 100 Index

FTSE 100 Index					
***N* = 2,524**	**Mean**	**Standard Deviation**	**Skewness** [a]	**Excess Kurtosis** [a]	**J-B Test** [b]
1992	0.0006	0.0099	0.9440***	5.8407***	*RNor*
1993	0.0007	0.0063	0.2536	0.8816***	*RNor*
1994	-0.0004	0.0085	-0.1616	-0.5249	*Nor*
1995	0.0008	0.0062	0.0010	0.4668	*Nor*
1996	0.0004	0.0060	-0.4022***	0.3198	*RNor*
1997	0.0010	0.0095	-0.1524	0.9105***	*RNor*
1998	0.0006	0.0134	0.0076	0.8724***	*RNor*
1999	0.0006	0.0116	-0.1388	0.3353	*Nor*
2000	-0.0002	0.0118	-0.0346	-0.1671	*Nor*
2001	-0.0006	0.0133	-0.0154	0.5046*	*RNor*
Overall	0.0003	0.0100	0.0056	1.8644***	*RNor*

[a] To compute skewness (Sk) and excess kurtosis (Ku) and to test for significance (*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively) the following equations were used

Skewness and Excess Kurtosis Estimates: $Sk = \frac{N^2}{(N-1)(N-2)}\frac{m_3}{s^3}$, $Ku = \frac{N^2}{(N-1)(N-2)(N-3)}\frac{(N+1)m_4 - 3(N-1)m_2^2}{s^4}$

Significance Test: $Sk = 0; z = Sk\left[\frac{(N-1)(N-2)}{6N}\right]^{1/2}$, $Ku = 0; z = Ku\left[\frac{(N-1)(N-2)(N-3)}{24N(N+1)}\right]^{1/2}$

where s = standard deviation and $m_k = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^k$

[b] *J-B Test* is the Jarque-Bera test for normality. *Nor* is where the normality hypothesis is not rejected at the 5% level of significance. *RNor* is where normality is rejected at the 5% level of significance.

Table 2: Summary Statistics for Daily Arithmetic Returns Data on ESX Option Bins [a]

	Option Characteristics			Mean	Std. Dev	Skewness	Kurtosis	Avg. Vol. [b]	J-B Test [c]
	Delta	**Class.**	**Nearby**						
Calls	**0.15 to 0.30**	**OTM 2**	**1**	-0.0023	0.3381	1.0470	5.9568	197	*RNor*
Calls	**0.30 to 0.45**	**OTM 1**	**1**	-0.0016	0.2743	0.7136	4.3422	172	*RNor*
Calls	**0.45 to 0.60**	**ATM 1**	**1**	-0.0018	0.2204	0.4267	3.5404	160	*RNor*
Calls	**0.60 to 0.75**	**ITM 1**	**1**	-0.0002	0.1727	0.2711	3.4806	29	*RNor*
Calls	**0.75 to 0.90**	**ITM 2**	**1**	0.0007	0.1170	0.0767	3.6728	7	*RNor*
Calls	**0.15 to 0.30**	**OTM 2**	**2**	-0.0021	0.2365	0.5907	3.7363	62	*RNor*
Calls	**0.30 to 0.45**	**OTM 1**	**2**	-0.0005	0.1912	0.4137	3.3848	76	*RNor*
Calls	**0.45 to 0.60**	**ATM 1**	**2**	0.0000	0.1541	0.2579	3.1803	83	*RNor*
Calls	**0.60 to 0.75**	**ITM 1**	**2**	0.0007	0.1202	0.1678	3.3093	16	*RNor*
Calls	**0.75 to 0.90**	**ITM 2**	**2**	0.0010	0.0819	0.0082	3.2869	2	*Nor*
	Underlying			0.0003	0.0105	0.0193	4.3251	-	*RNor*
	Option Characteristics			**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**	**Avg. Vol. [b]**	**J-B Test [c]**
	Delta	**Class.**							
Puts	**-0.75 to -0.90**	**ITM 2**	**1**	-0.0027	0.1769	0.4283	3.4916	11	*RNor*
Puts	**-0.60 to -0.75**	**ITM 1**	**1**	-0.0041	0.2132	0.5909	3.8223	46	*RNor*
Puts	**-0.45 to -0.60**	**ATM 1**	**1**	-0.0065	0.2509	0.8131	4.5213	202	*RNor*
Puts	**-0.30 to -0.45**	**OTM 1**	**1**	-0.0097	0.2898	1.0305	5.2338	174	*RNor*
Puts	**-0.15 to -0.30**	**OTM 2**	**1**	-0.0151	0.3365	1.4045	6.9048	160	*RNor*
Puts	**-0.75 to -0.90**	**ITM 2**	**2**	-0.0019	0.1250	0.3616	3.3197	3	*RNor*
Puts	**-0.60 to -0.75**	**ITM 1**	**2**	-0.0029	0.1488	0.4733	3.5103	12	*RNor*
Puts	**-0.45 to -0.60**	**ATM 1**	**2**	-0.0038	0.1734	0.6335	3.9125	89	*RNor*
Puts	**-0.30 to -0.45**	**OTM 1**	**2**	-0.0056	0.1989	0.8027	4.3975	87	*RNor*
Puts	**-0.15 to -0.30**	**OTM 2**	**2**	-0.0080	0.2314	1.0744	5.4931	59	*RNor*

[a] As part of the data filtering process we only use days where there is a return observation for *all* bins. As a result each bin contains 1,729 observations.
[b] The volume figure reported is calculated using bins data prior to filtering for problematic days (each bin contains 1,793 observations).
[c] *J-B Test* is the Jarque-Bera test for normality. *Nor* = Fail to reject normality; *RNor* = Reject normality (at the 5% level of significance)

Table 3: Summary Systematic Moment Statistics for ESX Option Data

	Option Characteristics			Systematic Variance			Systematic Kurtosis	
	Delta	**Class.**	**Nearby**	β [a]	*BS-*β [b]	*MW-*β [c]	δ[a]	δ[d]
Calls	**0.15 to 0.30**	**OTM 2**	**1**	34.29	34.95	0.26	32.92	-0.18
	0.30 to 0.45	**OTM 1**	**1**	28.66	28.43	0.41	27.69	-0.00
	0.45 to 0.60	**ATM 1**	**1**	23.47	22.83	0.57	22.88	0.21
	0.60 to 0.75	**ITM 1**	**1**	18.39	17.56	0.74	18.07	0.31
	0.75 to 0.90	**ITM 2**	**1**	12.45	11.69	0.92	12.36	0.32
	0.15 to 0.30	**OTM 2**	**2**	24.40	24.55	0.26	23.56	-0.05
	0.30 to 0.45	**OTM 1**	**2**	20.02	19.79	0.41	19.46	0.09
	0.45 to 0.60	**ATM 1**	**2**	16.36	15.90	0.57	16.00	0.19
	0.60 to 0.75	**ITM 1**	**2**	12.74	12.21	0.74	12.51	0.20
	0.75 to 0.90	**ITM 2**	**2**	8.69	8.23	0.91	8.59	0.19
	Option Characteristics			Systematic Variance			Systematic Kurtosis	
	Delta	**Class.**	**Nearby**	β [a]	*BS-*β [b]	*MW-*β [c]	δ[a]	δ[d]
Puts	**-0.75 to -0.90**	**ITM 2**	**1**	-18.43	-17.10	-0.84	-17.79	0.02
	-0.60 to -0.75	**ITM 1**	**1**	-22.11	-20.20	-0.70	-21.37	-0.01
	-0.45 to -0.60	**ATM 1**	**1**	-25.73	-23.14	-0.55	-24.91	-0.05
	-0.30 to -0.45	**OTM 1**	**1**	-29.27	-26.03	-0.38	-28.28	0.02
	-0.15 to -0.30	**OTM 2**	**1**	-32.65	-29.14	-0.20	-31.85	-0.26
	-0.75 to -0.90	**ITM 2**	**2**	-13.01	-12.12	-0.83	-12.63	-0.07
	-0.60 to -0.75	**ITM 1**	**2**	-15.44	-14.94	-0.69	-15.01	-0.11
	-0.45 to -0.60	**ATM 1**	**2**	-17.83	-16.16	-0.53	-17.40	-0.20
	-0.30 to -0.45	**OTM 1**	**2**	-20.22	-18.07	-0.37	-19.78	-0.27
	-0.15 to -0.30	**OTM 2**	**2**	-22.92	-20.14	-0.19	-22.54	-0.42

[a] The systematic variance and systematic kurtosis figures reported are average values calculated using the equations below. (N = 1,610)

$$\tilde{\beta}_j = \left[\sum_t \left(\tilde{R}_{jt} - \overline{R}_{jt}\right)\left(\tilde{R}_{mt} - \overline{R}_{mt}\right)\right] / \sum_t \left[\left(R_{mt} - \overline{R}_{mt}\right)^2\right]$$

$$\tilde{\delta}_j = \left[\sum_t \left(\tilde{R}_{jt} - \overline{R}_{jt}\right)\left(\tilde{R}_{mt} - \overline{R}_{mt}\right)^3\right] / \sum_t \left[\left(R_{mt} - \overline{R}_{mt}\right)^4\right]$$

[b] The *BS-*β figures reported are average Black-Scholes betas calculated using the following equations (N = 1,793).

$$BS(\beta_c) = \beta_i * N(d_1) * \frac{I}{C}$$

$$BS(\beta_p) = \beta_i * [N(d_1) - 1] * \frac{I}{P}$$

[c] The *MW-*β figures reported are from regressions (N = 1,729) where money-weighted call returns were regressed on money-weighted index returns.

$$R_c * C(P) = \alpha + \beta(R_i * I) \quad or$$

$$\Delta C(P) = \alpha + \beta(\Delta I)$$

The term on the left hand side is the change in the price of the call/put and the term on the right hand side is the change in the level of the FTSE 100 index. Because these regressions are run using absolute movements in the option and the underlying the results are of different scale to the other estimates of systematic variance.

[d] When using higher moments as regressors problems of collinearity arise when estimating the systematic moments. This is particularly evident in the systematic variance and systematic kurtosis estimates. The solution is to orthogonalise the systematic kurtosis estimate with respect to the systematic variance estimate by estimating what might be termed *co-excess kurtosis* as follows.

$$\tilde{\delta}_j = \sum_t \left[(\tilde{R}_{jt} - \overline{R}_{jt})\right]\left[(\tilde{R}_{mt} - \overline{R}_{mt})^3 - 3\sigma^2(\tilde{R}_{mt} - \overline{R}_{mt})\right] / \sum_t \left[(\tilde{R}_{mt} - \overline{R}_{mt})^4\right]$$

Table 4: Classic Cross-Sectional Regression Results

	Model I		Model II[a]			Model III[a]	
N **= 1,610**	$R_{jt} - R_{ft} = \alpha_0 + \alpha_1 \beta_{jt}$		$R_{jt} - R_{ft} = \alpha_0 + \alpha_1 \beta_{jt} + \alpha_2 \delta_{jt}$			$R_{jt} - R_{ft} = \alpha_0 + \alpha_2 \delta_{jt}$	
ALL	α_0	α_1	α_0	α_1	α_2	α_0	α_2
Mean α[b]	-0.0040***	-0.0000	-0.0018***	0.0004	0.0056***	-0.0027	-0.0027
***t*-stat**[c]	-4.23	-0.08	-3.45	0.90	3.46	-1.42	-0.72
Adj. R^2	0.8543		0.9145			0.7046	
CALLS	α_0	α_1	α_0	α_1	α_2	α_0	α_2
Mean α	-0.0031***	-0.0006*	0.0029**	-0.0006	-0.0002	0.0012	-0.0023
***t*-stat**	-2.77	-1.95	2.49	-1.33	-0.11	0.44	-0.51
Adj. R^2	0.8059		0.8410			0.6697	
PUTS	α_0	α_1	α_0	α_1	α_2	α_0	α_2
Mean α	0.0073***	0.0007**	0.0031*	0.0010***	0.0079***	0.0023	-0.0045**
***t*-stat**	4.00	2.24	1.70	2.58	4.40	0.65	-1.99
Adj. R^2	0.7167		0.8088			0.5399	

[a] The kurtosis measure employed in the regressions is the orthogonalised kurtosis estimate described earlier.
[b] The slope coefficients reported are means for all of the daily cross-sectional regressions
[c] The *t*-values are equal to the mean value of the coefficient divided by its standard deviation. This tests whether the coefficient value is significantly different from zero.
*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 5: Upday/Downday Regression Results

	α_0	α_1	α_2	Adj. R^2	N
CALLS: UPDAYS					
Model I $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}$	0.0031*[b] (1.78)[c]	0.0072*** (20.07)	- -	0.7480	826
Model II[a] $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}+\alpha_2\delta_{jt}$	0.0038** (2.18)	0.0069*** (11.49)	-0.0031 (-0.97)	0.7892	826
Model III[a] $R_{jt}-R_{ft}=\alpha_0+\alpha_2\delta_{jt}$	0.0364*** (9.68)	- -	-0.0304*** (-4.65)	0.6230	826
CALLS: DOWNDAYS					
Model I $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}$	0.0032** (2.20)	-0.0088*** (-37.89)	- -	0.8668	784
Model II $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}+\alpha_2\delta_{jt}$	0.0019 (1.28)	-0.0085*** (-15.65)	0.0028 (1.03)	0.8956	784
Model III $R_{jt}-R_{ft}=\alpha_0+\alpha_2\delta_{jt}$	-0.0359*** (-10.11)	- -	0.0274*** (4.87)	0.7190	784
PUTS: UPDAYS					
Model I $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}$	0.0035* (1.85)	0.0081*** (38.24)	- -	0.7968	826
Model II $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}+\alpha_2\delta_{jt}$	-0.0013 (-0.58)	0.0085*** (25.08)	0.0043** (2.19)	0.8582	826
Model III $R_{jt}-R_{ft}=\alpha_0+\alpha_2\delta_{jt}$	-0.0671*** (-17.83)	- -	-0.0027 (-0.93)	0.5882	826
PUTS: DOWNDAYS					
Model I $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}$	0.0113*** (3.57)	-0.0072*** (-16.57)	- -	0.6324	784
Model II $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}+\alpha_2\delta_{jt}$	0.0078*** (2.61)	-0.0069*** (-11.86)	0.0116*** (3.83)	0.7568	784
Model III $R_{jt}-R_{ft}=\alpha_0+\alpha_2\delta_{jt}$	0.0754*** (15.41)	- -	-0.0065* (-1.82)	0.4891	784
ALL: UPDAYS					
Model I $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}$	-0.0034*** (-2.91)	0.0076*** (31.84)	- -	0.8548	826
Model II $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}+\alpha_2\delta_{jt}$	-0.0022*** (-3.24)	0.0083*** (21.12)	0.0050** (2.54)	0.9142	826
Model III $R_{jt}-R_{ft}=\alpha_0+\alpha_2\delta_{jt}$	-0.0016 (-0.61)	- -	-0.0072 (-1.29)	0.7017	826
ALL: DOWNDAYS					
Model I $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}$	-0.0045*** (-3.07)	-0.0081*** (-29.87)	- -	0.8538	784
Model II $R_{jt}-R_{ft}=\alpha_0+\alpha_1\beta_{jt}+\alpha_2\delta_{jt}$	-0.0015* (-1.76)	-0.0080*** (-14.05)	0.0061** (2.39)	0.9149	784
Model III $R_{jt}-R_{ft}=\alpha_0+\alpha_2\delta_{jt}$	-0.0039 (-1.39)	- -	0.0020 (0.39)	0.7016	784

[a] The kurtosis measure employed in the regressions is the orthogonalised kurtosis estimate described earlier.
[b] The slope coefficients reported are means for all of the daily cross-sectional regressions
[c] The *t*-values (in parentheses) are equal to the mean value of the coefficient divided by its standard deviation. This tests whether the coefficient value is significantly different from zero.
*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively

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[25] The risk-free rate of interest used is an overnight inter-bank rate. This data was obtained from Datastream.
[26] Equivalently, the delta space measure can be viewed as a measure of an option's moneyness.

[27] LIFFE uses a modified version of Black-Scholes, which they term the Black-I model. Since the ESX option is European it can only be exercised on the last trading day, and as a result is priced as though it is an option on the future. The underlying value for the ESX option is an implied FTSE 100 index future.
[28] The volatility figure used in the delta calculation is an *implied volatility* estimate provided by LIFFE.
[29] We calculate a number of alternative measures of systematic variance, systematic skewness and systematic kurtosis for reasons that become apparent as the study evolves.
[30] The two-step, time-series, cross-sectional approach gives rise to an errors-in-variable problem as our regressor estimates for β , γ , and δ are measured with error. Ferson, W. and Jagannathan R. (1996) 'Econometric Evaluation of Asset Pricing Models', in the Handbook of Statistics: vol. 14: Statistical Methods in Finance, G.S. Maddala and C.R. Rao (eds), North Holland point out that using finite time-series samples for the estimation of the regressors will result in inconsistent coefficient estimates, even if the cross-sectional sample is infinite. However, they also note that the cross-sectional regression will provide consistent estimates of the coefficients as the time-series sample becomes very large because the first step estimate of the regressors is consistent, so as the time-series sample size becomes large, the errors-in-variables problem of the second-stage regression disappears. Shanken, J. (1992) 'On the Estimation of Beta Pricing Models', *Review of Financial Studies*, 5, 1-34 however warns that the estimation error cannot be ignored even if the estimation error disappears in the limit.
[31] See Appendix A for more detailed descriptions of the data fields.
[32] Furthermore, from a time-to-expiration perspective *nearby* contracts are most heavily traded with very little activity in longer dated contracts.
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[34] Bondarenko, O. (2003) 'Why Are Put Options So Expensive', Working Paper, University of Illinois at Chicago notes that "because puts are negatively correlated with the market, it is not surprising that they are traded at negative risk premiums" and that " because of the considerable leverage, the magnitude of those risk premiums is expected to be large."
[35] In our case we are using the delta-space measure that we outlined in the Methodology section.
[36] The use of arithmetic returns is justified on the basis that "because options held to maturity often have net returns of –1 (i.e., expire worthless), the log-transformation of any set of option returns over any finite holding period will be significantly lower than the raw net returns."
[37] Shiekh, A. and Ronn, E. (1994) 'A Characterisation of the Daily and Intraday Behaviour of Returns on Options', *Journal of Finance*, 49, 557-579.
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[39] First nearby options are identified by comparing an option's trade date with its expiration date. Where an option's trade date is in January and its expiration date in February, for example, it is identified for first nearby bins. First nearby options have, on average, 34 days to expiration, a minimum time to expiration of 15 days and a maximum time to expiration 51 days,
[40] Like first nearby options, second nearby options are identified by comparing the option's trade date with its expiration date. For example, if the trade date is in August and the expiration date in October then such an option is identified as second nearby. Second nearby options have, on average, 63 days to expiration, a minimum time to expiration of 44 days and a maximum time to expiration 81 days
[41] See Appendix A for definition.
[42] Yadav, P. and Pope, P. (1990) 'Stock Index Futures Arbitrage: International Evidence', *Journal of Futures Markets*, 10, 573-603.
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[46] It should be noted that for some of the years in the dataset the reported closing price is inconsistent with the bid-ask spread reported.