2006-01-01

Re-evaluating Hedging Performance

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Recommended Citation

Hanly, J., Cotter, J.: Re-evaluating Hedging Performance. Journal of Futures Markets, 26 (7): 677-702

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May 30th 2005

Abstract

Mixed results have been documented for the performance of hedging strategies using futures. This paper reinvestigates this issue using an extensive set of performance evaluation metrics across seven international markets. We compare the hedging performance of short and long hedgers using traditional variance based approaches together with modern risk management techniques including Value at Risk, Conditional Value at Risk and approaches based on Downside Risk. Our findings indicate that using these metrics to evaluate hedging performance, yields differences in terms of best hedging strategy as compared with the traditional variance measure. We also find significant differences in performance between short and long hedgers. These results are observed both in-sample and out-of-sample.

Keywords: Hedging Performance; Lower Partial Moments; Downside Risk; Variance; Semi-Variance; Value at Risk, Conditional Value at Risk.

JEL classification: G10, G12, G15.

1. Introduction

Hedging with futures contracts is perhaps the simplest method for managing market risk arising from adverse movements in the price of various assets. The success of a hedging strategy is measured by the extent to which it reduces risk, and many techniques have been developed and applied to find the optimal investment in futures – the optimal hedge ratio (OHR) with the aim of reducing risk. A large body of research has developed in the calculation and evaluation of optimal hedging strategies (see, for example, Kroner and Sultan 1993; Park and Switzer 1995; Choudhry, 2003). The literature on optimal hedging indicates that OHR's estimated by OLS generally yield the best results in-sample. There is little performance difference between models in an out-of sample context, however, with both OLS and GARCH models failing to significantly outperform the simple naïve hedge (see, for example Brooks et al, 2002). It is not clear, however, whether the general results on model hedging effectiveness are specific to the narrow performance appraisal criteria that have been applied in the literature (namely the variance) or whether these results hold under a broad range of hedging performance metrics. The evaluation of hedging strategies has been overwhelmingly based on the objective of minimising variance and therefore the general results on hedging efficiency reflect models that achieve variance minimisation as their stated aim.

A key issue not extensively explored in the literature is whether the estimates of hedging effectiveness of optimal hedging strategies for many applied models would change if performance criteria other than the variance were to be applied. The use of variance or standard deviation as measures of risk have been criticised because negative and positive returns are given equal weight, whereas a measure of hedging effectiveness that incorporates trading position and differentiates between positive and negative outcomes may be more appropriate. Such a measure would need to be one-sided in nature so that it can distinguish between downside and upside risks that are relevant to short and long hedgers respectively. This paper addresses this issue of performance evaluation in a number of ways.

First, we evaluate and compare hedging strategies using five different performance metrics. These are the Variance, Semi-Variance; Lower Partial Moments (LPM); Value at Risk (VaR) and Conditional Value at Risk (CVaR). With the exception of the first metric, these performance metrics are tail specific. Second, we examine hedging effectiveness across a number of different hedging strategies including, a no hedge strategy; a naïve approach, and a model based hedging approach. We use three models to calculate the OHR. These are OLS using a rolling window approach, and two time-varying multivariate GARCH approaches; the Diagonal VECH and the Constant Correlation models. This gives a total of five hedging strategies. Third, we apply each of the above metrics for both short and long hedgers across seven leading stock index spot and futures contracts. This approach allows us to examine whether the dominance of Naïve and OLS based hedging strategies is specific to the use of the variance reduction criterion or whether different performance metrics favour different hedging strategies. To anticipate our results, we find that while the overall dominance of Naïve and OLS based hedging strategies is confirmed, in certain cases the use of performance metrics other than the variance may result in GARCH models being chosen as the best performing hedging methods. This is particularly true of the Value at Risk performance metric. Furthermore, we also find substantial differences in the hedging performance of short as opposed to long hedgers. This suggests that the hedging objectives and trading position of an investor should be considered when choosing a performance metric that is appropriate for evaluating the performance of different hedging strategies.

The remainder of this paper proceeds as follows. In Section 2 we describe the metrics for evaluating hedging performance. Section 3 details the models used for estimating optimal hedge ratios. Section 4 describes the data and presents some summary statistics. Section 5 presents our empirical findings on hedging performance. Section 6 summarises and concludes.

2. Performance Metrics

We examine the in-sample and out-of-sample hedging performance of five hedging strategies using five different metrics of performance. Our performance metrics are based on the Variance, the Semi-Variance, LPM, VaR, and CVaR. The hedging strategies we use are no hedge, a naïve hedge, and a model based hedge where three different models are used to estimate the OHR: Rolling OLS, Diagonal Vector GARCH (DVECH) and Constant Correlation GARCH (CC).

2.1 Hedging Effectiveness Metric 1 - The Variance

The first performance metric we use to examine hedging performance is the variance. The variance metric (HE_1) that we use measures the percentage reduction in the variance of a hedged portfolio as compared with the variance of an unhedged portfolio. The hedged portfolios are calculated by using the OHR's derived from our hedging models, with the best model being the one with the largest reduction in the variance. The performance metric is:

$$HE_1 = 1 - \left[\frac{VARIANCE_{HedgedPortfolio}}{VARIANCE_{UnhedgedPortfolio}} \right] \tag{1}$$

This gives us the percentage reduction in the variance of the hedged portfolio as compared with the unhedged portfolio. When the futures contract completely eliminates risk, we obtain $HE_1 = 1$ which indicates a 100% reduction in the variance, whereas we obtain $HE_1 = 0$ when hedging with the futures contract does not reduce risk. Therefore, a larger number indicates better hedging performance[1].

The variance is a standard measure of risk in finance and has become the dominant measure of hedging effectiveness used by hedgers. It has also been extensively applied in the literature on hedging and was used by Ederington (1979) to evaluate hedging effectiveness. The advantage of using the variance as a measure of performance is its ease of calculation and interpretation. However, there are a number of problems with its use as a hedging performance metric. Firstly, because the variance is a two-sided measure that attaches the same weight to both positive and negative returns, it does not distinguish between upside and downside probabilities. This may not be efficient since hedgers are concerned with the probabilities associated with a single tail of the return distribution. Secondly, when return distributions are non-normal, as is standard for financial returns, we require more than the first two moments to adequately characterise the distribution. Thus we also use a number of alternative performance metrics.

2.2 Hedging Effectiveness Metric 2 - The Semi Variance

The semi-variance, which measures the variability of returns below the mean was used as a measure of risk following work by Roy (1952) who developed the safety first criterion. This introduced the concept of an investor preferring to minimise the probability of falling below some predefined level of return, termed the disaster level. A more general approach to downside risk developed from this, which specified risk in terms of probability weighted functions of deviations below some target level of return. The semi-variance is the first of a class of downside risk measures that we use and is presented here as a special case of the more general LPM discussed later. It is calculated as:

$$\text{Semi-Variance}= E\left\{(\max[0, \tau - R])^2\right\} = \int_{-\infty}^{\tau} (\tau - R)^2 \, dF(R) \qquad (2)$$

where τ, the target return is set to the expected return, R is the return on the hedged portfolio and F is the distribution function of R. In the downside risk framework the weighting that is attached to deviations from the target rate of return is based on an investors risk preference. For the semi-variance, the deviations from the target return $(\tau - R)$ are squared. When the distribution is symmetric and the target return is set to the mean, the semi-variance is equivalent to half the variance. For a non-symmetric distribution, however, the semi-variance can distinguish between the tails of the distribution. It therefore addresses the primary shortcoming of the variance and provides a more intuitive measure of risk for hedging as it focuses on downside risk. However it does not distinguish between investors who may have different risk preferences since only one weighting is attached to deviations from the mean. The performance metric that we use is the percentage reduction in the semi-variance of our hedge strategies as compared with a no hedge position.

$$HE_2 = 1 - \left[\frac{Semi - \mathrm{var}\,iance_{HedgedPortfolio}}{Semi - \mathrm{var}\,iance_{UnhedgedPortfolio}} \right] \qquad (3)$$

2.3 Hedging Effectiveness Metric 3 - The Lower Partial Moment

The development of the LPM was an important development in the area of downside risk measures and is attributed to Bawa (1975) who introduced a general definition of downside risk, and Fishburn (1977) who developed the (α,t) model. The lower partial moment of order *n* around τ is defined as

$$\mathrm{LPM}_n(\tau;R) = E\left\{(\max[0, \tau - R])^n\right\} \equiv \int_{-\infty}^{\tau} (\tau - R)^n \, dF(R) \qquad (4)$$

where F(R) is the cumulative distribution function of the investment return R and τ is the target return parameter. Note that if n=2 and τ is set to the mean, then (4) is equivalent to the semi-variance (3). In practice the value of τ will depend on an investor's minimum acceptable level of return. Some values of τ that may be considered are zero, or the risk free rate of interest. The parameter n reflects the amount of weight an investor will attach to the shortfall from the target return. An investor who is more concerned with extreme shortfalls would assign a higher weight which would be represented by higher values of n. Fishburn (1977) shows that $0 < n < 1$ is suitable for a risk seeking investor, $n = 1$ for risk neutral, and $n > 1$ for a risk averse investor. By changing these parameters we can form a complete set of downside risk measures. There are a number of advantages of using LPM to examine performance in a hedging context. Firstly, since the LPM is estimated as a function of the underlying distribution, it has been shown to be robust to non-normality (Bawa, 1975). This is an important advantage of the LPM framework in that it does not require the assumption of normality in the return distribution, and can therefore estimate tail probabilities for assets whose return distributions are non-normal. Secondly, an analysis of differential hedging performance may reveal information regarding the asymmetry of the joint distribution of spot and futures returns for a given asset. Therefore, a downside risk approach using LPM addresses the primary shortcoming of the traditional variance based measure of hedging performance. This is especially important for short and long hedgers, as each type of investor would minimize the associated risk measure over the opposite portions of the return distribution of the hedge portfolio.

Recently, a number of studies have examined hedging using the LPM methodology (see, for example Lien and Tse, 2002 for a comprehensive survey). The literature on the applications of LPM to futures hedging generally deals with the calculation of minimum LPM hedge ratios and compares these ratios to the traditional minimum variance hedge ratios. Also, Lien and Demirer (2003) calculate OHR's designed to minimise the LPM, however their focus is on the relationship between the inputs into the LPM calculations and the effects on the resulting OHR. Examining their findings indicates similar levels of performance across differing values of *n*. A more recent paper by Demirer et al (2005) investigates hedging performance using a number of risk measures including LPM. The results from these studies indicate that long hedgers tend to gain more benefit than short hedgers, as measured by the percentage reduction in the LPM's of their hedged portfolios. In both papers, the measure of hedging effectiveness is based on the methodology used to estimate the OHR. For example, where the LPM minimising OHR is estimated, the measure of hedging effectiveness used is the percentage reduction in the LPM of the portfolios constructed using that OHR. However, no study has applied LPM based performance measures to evaluate optimal hedging strategies based on OLS or GARCH models.

We calculate the lower partial moment as DSR measures, using n=3, which corresponds to a risk averse investor[2]. The target return τ used in the LPM function is linked to an investor's stated aim. From a risk management perspective the aim of a hedger is to avoid negative outcomes, therefore we use a target return $\tau = 0$. The performance metric that we use is the percentage reduction in the LPM of our hedge strategies over a no hedge position. This is calculated as:

$$HE_3 = 1 - \left[\frac{LPM_{3\,HedgedPortfolio}}{LPM_{3\,UnhedgedPortfolio}} \right] \tag{5}$$

2.4 Hedging Effectiveness Metric 4 – Value at Risk

The fourth metric we use to gauge hedging effectiveness is VaR. The use of VaR as a method of evaluating hedge strategies is relatively new, although Brooks et al (2002) analyse the impact of asymmetry on time varying hedges using an alternative performance metric, based on Minimum Capital Risk Requirements (MCRR's), which is a VaR based approach. We use VaR because it determines the maximum size of losses associated with the hedging strategy and also because of its increasing use as a measure of risk, both for internal risk management models and for regulatory requirements. VaR estimates the probability of a loss that may occur as a result of changes in the value of a security or portfolio. VaR has two parameters, the time horizon (N) and the confidence level (x). Generally VaR is the (100-x)th percentile of the return distribution of the change in the asset or portfolio over the next N days. Using equation (4) with $n = 0$, we calculate VaR as a special case of the LPM approach. By fixing the probability LPM_0, the corresponding VaR can be calculated.

$$VaR = F^{-1}(LPM_0) \tag{6}$$

The cumulative distribution function F(R) is the probability of the portfolio return R being less than a given value (τ) which is exogenous. Therefore, VaR gives us the return that is exceeded with (100-x) % probability. It is possible, however, that two portfolios will have the same VaR but with different potential losses. This is because VaR does not account for losses beyond the (100-x)th percentile. We address this shortcoming by estimating an additional performance metric (CVaR) which is outlined in the next section. We calculate VaR using the 1% confidence level under which we would expect losses in excess of the VaR to occur once every N days. The performance metric employed is the percentage reduction in VaR.

$$HE_4 = 1 - \left[\frac{VaR_{1\%\,HedgedPortfolio}}{VaR_{1\%\,UnhedgedPortfolio}} \right] \tag{7}$$

2.5 Hedging Effectiveness Metric 5 – Conditional Value at Risk

The fifth performance metric is CVaR. This measures the mean loss, conditional that we have exceeded the VaR. We use CVaR as a hedging performance metric because it provides a hedger with an estimate not only of the probability of a loss, but also of the magnitude of a possible loss (for further details see Tasche, 2002). We calculate CVaR as a special case of LPM with *n*=1 and the minimum return τ set to the VaR. This gives us the CVaR which is sometimes referred to as the expected or target shortfall.

$$CVaR = \int_{-\infty}^{\tau} (\tau - R)^1 \, dF(R) \tag{8}$$

In calculating CVaR we again use the 1% confidence level to examine the position for different types of hedgers. The performance metric we use to evaluate hedging effectiveness is the percentage reduction in CVaR.

$$HE_5 = 1 - \left[\frac{CVaR_{1\%\,HedgedPortfolio}}{CVaR_{1\%\,UnhedgedPortfolio}} \right] \tag{9}$$

In this section we have outlined five different performance metrics (Variance, Semi-variance, LPM, VaR and CVaR). These include the dominant variance measure, but also include metrics that allow a comprehensive comparison of the best hedging strategies for different types of hedger and different trading positions. Now we outline the five hedging strategies and the models used to estimate the OHR.

3. Hedging Models

The aim of hedging is to reduce the risk of investing in one financial asset by taking an offsetting position in another financial asset. In this paper we consider stock index and stock index futures contracts. The OHR - the hedge ratio that minimises risk, is the slope coefficient β obtained by a regression of the change in the spot price against the change in the futures price. This is given by:

$$r_{st} = \alpha + \beta r_{ft} + \varepsilon_t \qquad (10)$$

where r_{st} and r_{ft} are the spot and futures returns respectively for period t, and ε_t is the disturbance term. This regression estimation with OLS was first used by Ederington (1979) and has been applied extensively in the literature. However, this method assumes that the second moments do not change over time, whereas numerous studies (see, for example, Cecchetti et al., 1988, Baillie and Myers, 1991) have found that the joint distribution of spot and futures returns is time-varying and therefore the hedge ratio is estimated incorrectly. Time-varying volatility is the rule for financial time series and as the optimal hedge ratio depends on the conditional distribution of spot and futures returns, so too should the hedge ratio. Five hedging strategies are used therefore, three of which allow for time variation in the return distribution. The hedging strategies used are: No Hedge, Naïve Hedge, and an OHR estimated by; Rolling Window OLS; DVECH GARCH; and CC GARCH. This allows a broad comparison in terms of hedging performance over a range of hedging models.

3.1 No Hedge

This assumes that the exposure is left unhedged and is used as a performance benchmark. This is included as many firms and financial market participants choose not to hedge their exposures since hedging reduces not only risk, but also the expected return to bearing that risk.

3.2 Naïve Hedge

This involves adopting a futures position equal in magnitude but opposite in sign to the spot position being hedged. The hedge ratio is therefore -1 at all times. The advantage of this method is its simplicity, although it will not minimise risk unless both spot and futures positions are perfectly correlated.

3.3 Rolling Window OLS

The first model we use to account for time variation is a rolling window OLS model. This estimates the hedge ratio by conditioning on recent information using a rolling window estimator of the variance-covariance matrix. Hedge ratios are re-estimated on a day-by-day basis whereby the most recent observation is added and the oldest observation is removed, thus keeping the number of estimation observations unchanged. The advantage of this method from a hedging perspective is that by updating the information set we obtain a more efficient estimate of the hedge ratio, which takes time variation in the return distribution into account. However, in common with other methods that require the hedge ratio to be time-varying, it may be expensive as changing the hedge ratio increases transactions costs.

3.4 GARCH Models

Strategies to account for time variation using the GARCH class of models have become prevalent (see, for example, Bollerslev, 1986, 1990). In general, GARCH models assume that the conditional variance of returns is affected by its own history and the history of the squared innovations (changes) in returns. The advantage of GARCH models is that they have been able to capture the behaviour of financial time series, such as serial correlation in volatility and co-movements in volatilities. The large literature on optimal hedging has extensively used multivariate GARCH models to generate OHR's (see, for example, Kroner and Sultan, 1993; Lien et al, 2002). From a hedging perspective the multivariate GARCH class of models are particularly suitable, since they can estimate jointly the conditional variances and covariances required for optimal hedge ratios, and they have demonstrated good performance when used to generate forecasts of the variance-covariance matrix over short time horizons (Conrad et al, 1991, Engle and Kroner, 1995). On the other hand, the performance of the multivariate GARCH class of models has generally been poor when used to generate forecasts over longer hedging horizons (see, for example, Brooks et al, 2002, who also report, as stated, mixed results for out-of-sample performance when applying these models).

The Diagonal VECH GARCH Model (DVECH)

We apply two GARCH models to allow for an extensive comparison. The first GARCH model that we use is the Vector GARCH (1, 1) model proposed by Bollerslev, Engle and Woolridge (1988). The diagonal parameterisation of the VECH model has been used to generate OHR's by Baillie and Myers (1991) and Brooks and Chong (2001). This models the conditional mean and variance equations as follows:

$$r_{st} = \mu_s + \varepsilon_{st}$$

$$r_{ft} = \mu_f + \varepsilon_{ft}, \tag{11a}$$

$$\begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Omega_{t-1} \sim N\left(0, \sigma^2{}_t\right)$$

$$\sigma^2_{st} = \gamma_s + \alpha_s \varepsilon^2_{s,t-1} + \beta_s \sigma^2_{s,t-1} \tag{11b}$$

$$\sigma_{ft}^2 = \gamma_f + \alpha_f \varepsilon_{f,t-1}^2 + \beta_f \sigma_{f,t-1}^2 \qquad (11c)$$

$$\sigma_{sft} = \gamma_{sf} + \alpha_{sf} \varepsilon_{s,t-1,} \varepsilon_{f,t-1} + \beta_{sf} \sigma_{sf,t-1} \qquad (11d)$$

where r_{st} r_{ft} are the returns on spot and futures respectively, $\varepsilon_{st}, \varepsilon_{ft}$ are the residuals which represent the innovations in the spot and futures prices, Ω_{t-1} represents the information set at time t-1, $\sigma_{st}^2, \sigma_{ft}^2$ denotes the variance of spot and futures and σ_{sft} is the covariance between them, γ is an intercept term which is a 3x1 parameter vector, and α and β are 3x3 parameter matrices. This gives 21 parameters to be estimated (γ has 3 elements and α and β each have 9 elements). However, this model restricts the α and β matrices to be diagonal whereby only the upper triangular portion of the variance covariance matrix is used. This means that the conditional variance depends on past values of itself and past values of the squared innovations in returns. This reduces the number of parameters to 9 (now α and β each have 3 elements). This is subject to the requirement that the variance-covariance matrix is positive definite in order to generate positive hedge ratios.

The Constant Correlation GARCH Model (CC)

The second GARCH model we use is the Constant Correlation (CC) GARCH (1, 1) model introduced by Bollerslev (1990). The CC model has been applied extensively in a hedging context (Kroner and Sultan, 1993; Park and Switzer, 1995; Lien et al, 2002). The model is specified as follows:

$$r_{st} = \theta_{s0} + \sum_{j=1}^{J} \theta_{sj} r_{s,t-j} + \varepsilon_{st}\ ,\ r_{ft} = \theta_{f0} + \sum_{k=1}^{K} \theta_{fk} r_{f,t-k} + \varepsilon_{ft} \qquad (12a)$$

$$\begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} \Omega_{t-1} \sim N\left(0, \sigma^2{}_t\right)$$

$$\sigma_{st}^2 = \gamma_s + \alpha_s \varepsilon_{s,t-1}^2 + \beta_s \sigma_{s,t-1}^2 \tag{12b}$$

$$\sigma_{ft}^2 = \gamma_f + \alpha_f \varepsilon_{f,t-1}^2 + \beta_f \sigma_{f,t-1}^2 \tag{12c}$$

$$\sigma_{sft} = \rho \sigma_{st} \sigma_{ft} \tag{12d}$$

where $j,k = 1$ for a GARCH (1, 1) model, $\gamma, \alpha,$ and β are all positive, with $\alpha_i + \beta_i \leq 1$ for $i = s, f$. The conditional means follow an autoregressive process. The equations 12b and 12c maintain the assumptions of the Diagonal VECH model while the conditional correlation coefficient between spot and futures ρ in equation (12d) is constant. An advantage of the CC model is that it is positive semi-definite, subject to the conditional variances being positive. This is an important property for a model being used to generate hedge ratios as it means that the variance-covariance matrix is always non-negative. It is therefore easy to estimate and computationally efficient, which is a useful property as we re-estimate our model on a rolling window basis.

Using the models outlined, out-of-sample OHR's are computed using one-day-ahead forecasts of the variance's and covariances as estimated from each of the models. The parameters of the various GARCH models were estimated using the in-sample period comprising five years of data. Using these starting parameters, the forecasts of the conditional variance's and covariance's were then computed recursively using a constant sample size which was rolled forward by adding on the most recent observation and taking away the oldest. This method is similar in approach to Lien et al (2002). The resulting hedge ratios are used to compile hedge portfolios which are constructed as $+r_s - h^* r_f$ (short hedger) and $-r_s + h^* r_f$ (long hedger), where r_s and

r_f are the returns on the spot and futures respectively, and h^* is the estimated OHR. The five performance metrics outlined above are then used to provide a comprehensive comparison of the hedged portfolio returns over a one-day holding period, which is consistent with the OHR estimation.

4. Data Description

We use daily stock index and stock index futures contracts from seven major indices spanning the period 1 January 1998 – 31 December 2003. The data include two US, three European and two Asian equity markets indices. The indices chosen are: the S&P500 Composite, Dow Jones Industrials, DAX 30 KURS, CAC 40, Financial Times 100, Hang Seng, and Nikkei 225 Stock Average. These indices are representative of the most important equity stock and futures markets over a wide geographic and economic area. Since we evaluate hedging strategies using different performance evaluation methods, it is important that the hedging performance of the various models be consistent with some benchmark. Various studies (see, for example, Lien et al, 2002) have shown that hedging performance tends to be best over a short holding period. Daily data are therefore used, where returns are calculated as the differenced logarithmic prices. For each of the contracts the first five years observations were used to estimate the basic models and their diagnostics. The remaining one year of observations were used to facilitate out-of-sample comparisons. Summary statistics for the full sample are displayed in Table I. The means of the return series are generally negative with the exception of the DOW and the CAC40. Volatility as evidenced by standard deviation ranges from 1.3% to 2.1% with the Asian and European indices markedly higher than the American indices. All of the return series are non-normal as evidenced by large Bera-Jarque statistics and most of the series display significant kurtosis. The distribution of our return series is broadly similar within geographic regions. The HANGSENG shows the largest deviations from a Gaussian distribution as evidenced by excess kurtosis of 4.29 for the spot index and a correspondingly high Bera-Jarque statistic. All of the series exhibit conditional heteroskedasticity with significant LM test statistics. This is particularly noticeable in the European markets with the FTSE100 showing the most significant effects. This result justifies our decision to use methods that account for time variation. The data were checked for stationarity using Dickey Fuller unit root tests. We find that the raw series are non-stationary while the log return series are stationary. This is important from a hedging perspective as non-stationary series may lead to spurious regressions and therefore invalidate the estimation of optimal hedge ratios.

[INSERT TABLE I HERE]

5. Empirical Findings

The estimated in-sample model parameters for the Rolling OLS, DVECH and CC GARCH models are quite standard and are therefore not reproduced in detail[3], however, the following points were observed. The results of the Rolling OLS regression indicate positive significant coefficients on the futures returns which are the OHR estimates for this model. Both the DVECH and CC GARCH models appear to represent the conditional variance of the data quite well. The sum of the parameter estimates $\alpha_s + \beta_s$ for spot and $\alpha_f + \beta_f$ for futures is close to unity in most cases indicating strong volatility persistence. All of the coefficients in the models are strongly significant indicating the time-varying nature of the conditional variances and covariance's. Also, for all series the hedge ratios appear to be stationary. This result corroborates Brooks et al (2002) and indicates that there may be a narrow performance gap between the time varying and time invariant hedging approaches.

Table II presents the results of hedging performance for each hedging model for both short and long hedgers (Panel A, In-Sample and Panel B, Out-of-Sample).

[INSERT TABLE II HERE]

We compare the hedging performance of the different hedging strategies for each of the hedging effectiveness metrics HE_1 – HE_5 using Efrons (1979) bootstrap methodology. This involves the generation of a large number of sample datasets from the short and long data for each hedged portfolio. This enables us to test for statistical differences by employing t-tests of the differences between models based on the point estimates of our results. We do this for each market and for both short and long hedgers. For example, using the short hedged SP500 in-sample in column 1-HE_5, we compare the best performing OLS model with each of the other models. We therefore calculated 210 differences between the hedging models, together with their associated t-statistics both in-sample and out-of-sample. Of the 210 pairs tested, 170 (81%) are significant at the 1% level in-sample, whereas 140 (69%) are significant out-of sample. This indicates substantial differences in the statistical performance of the different hedging models across each of the different performance metrics.

Considering the overall hedging performance using HE_1 - the variance reduction criterion, both the in-sample and out-of-sample results show substantial reductions in variance for each of the hedge strategies as compared with a no-hedge position. In-sample, the clear winner in performance terms is the OLS model, which yields superior performance in each of our markets, followed by the two GARCH models. This result is consistent with other studies and is not surprising given that the OLS and GARCH models minimise the variance and are better able to fit the data in-sample (see, for example, Brooks and Chong, 2001). Out-of sample results show that both the Naïve and OLS strategies tend to outperform the GARCH models, however, the performance differences between the hedging strategies are not economically significant.

More generally we can see a number of features emerge when we examine performance using the performance measures other than the variance. Firstly, we can see that for each metric HE_2 – HE_5, both the in-sample and out-of-sample results of the hedging strategies illustrate the value of hedging in reducing risk, irrespective of the measure of risk employed. In-sample using HE_3 – the LPM for example, there are typical reductions in the LPM's of the hedged portfolio's ranging from around 70% to over 90% for each of the LPM's calculated. Also, using HE_4 - VaR, the results show large reductions in the VaR across all markets, and for both short and long hedgers. For example, a short hedger using the DVECH model to hedge the SP500 reduces the VaR by over 68% as compared with a no-hedge strategy. Similar results are found when we use HE_5 – CVaR. Also, out-of-sample results out-perform the in-sample results. This occurs in 96% of all cases and by an average of just over 8%. The only exceptions to this are the Long SP500 and NIKKEI for the VaR and CVaR metrics.

Secondly, performance differences between short and long hedgers were also compared. This was carried out as follows. Taking the SP500 for example, the hedging performance of the naïve model for short hedgers was compared against the naïve model for long hedgers. This was done for each market and for each performance metric excluding the variance, yielding 112 comparisons in total[4]. The results of this comparison indicate that short hedgers outperform long hedgers in 68% of cases in-sample and 64% of cases out-of-sample. The differences between short and long hedgers are more pronounced for some performance measures. For example, across all markets the average differences between model hedging effectiveness in-sample for the LPM, VaR and CVaR performance measures are 11%, 23% and 17% respectively as compared with just 4% for the Semi-Variance. This result is replicated out of sample and is consistent with those reported for short vs long hedgers in Demirer et al. (2005) and Lien and Demirer (2003).

Finally, we examine the results on a market by market basis finding economically significant performance differences both in-sample and out-of-sample between markets. Better performance is observed for the SP500, DOW and FTSE, while the worst hedging performance is observed for the DAX30. For example using performance metric HE_3 - the LPM, the DAX30 typically underperforms the SP500 by an average of around 27% in-sample and 5% out-of-sample. These performance differences are also observed on a model by model basis. Using the OLS model and performance metric HE_1 – the Variance, the best performing hedge in-sample is the FTSE100 (HE_1 94.9%) while the worst hedging performance is for the DAX30 (HE_1 72.7%). This represents a performance differential of over 30% and is consistent with lower correlation between the DAX30 spot and futures index as compared with the other markets. We also compare in-sample and out-of-sample results using an F-test of the ratio of the variances. The results are significantly different in all cases at the 5% level, with the out-of sample hedging performance better than-in-sample by an average of 6% across all hedging models and markets.

Table III provides a summary of model hedging performance for each of our stock market indices. This demonstrates that using different performance metrics to evaluate hedging strategies yields important differences in terms of which model is the most effective. If we examine the dominant hedging strategy in-sample and out-of sample for both short and long hedgers, we find substantial differences between the performance metrics. For example using the variance as our performance metric, the dominant hedging strategies are the Naïve and OLS models which together account for 93% of the best performing models. This drops to 82% when we use the semi-variance, 71% for both the LPM and CVaR metrics, whereas when we examine the best hedging model using the VaR performance metric, the GARCH models are the best performers in 54% of cases.

This has important implications for hedgers in that their performance criteria indicate which hedging model would be most appropriate in a given hedging context. Where hedgers have a variety of performance aims they should, therefore, consider a variety of measures of hedging effectiveness. Differences between markets also indicate that a different model may be chosen to generate a hedge strategy when a performance metric other than the variance is employed. More generally, the overall results indicate the superiority of the simpler rolling window OLS model in-sample and both the OLS and Naïve models out-of-sample. It would appear, therefore, that with the exception of the VaR metric, the dominance of these strategies is not specific to the use of the variance as a hedging performance metric.

[INSERT TABLE III HERE]

To verify our findings on the divergence of hedging effectiveness for the performance metrics applied, we again employ the bootstrap methodology. Table IV reports mean returns for the post sample hedge portfolios, together with statistical comparisons of performance results between hedging models. For each performance metric we compare each of the hedging models for both long and short hedgers with a benchmark hedge model which is the best performer (based on lowest dispersion). Specifically, let $\alpha_{ij} = \theta_{ij} - \theta$, where θ_{ij} is the $_i$th performance measure (Variance, Semi-variance, LPM, VaR, CVaR) for the $_j$th hedging model (None, Naïve, OLS, DVECH, CC) and θ is the benchmark performance measure. We test the null hypothesis $H_0 : \alpha_{ij} = 0$. For example, consider the CVaR (column 7) for the SP500 short hedger. We compare each CVaR with the benchmark best performer which is the CC hedge model. This is done for each contract and each performance metric. In this way we generate 280 comparisons between hedging models and their associated t-statistics. Of these, 131 of the pairs tested are significant at the 1% level (47%). This suggests that the performance differences reflect the out-of-sample performance differences of the hedge positions and is not the result of sample variation. Again we can see from Table IV the performance differences between a no hedge position and all the other hedge strategies.

[INSERT TABLE IV HERE]

Examining column 6 and 7 - the VaR and CVaR figures clearly show the benefits from hedging. Using the short hedged SP500 for example, the VaR figure indicates that there is a 1% chance of the unhedged portfolio losing more of 2.082% of its value, whereas the corresponding CVaR figure shows that the expected loss conditional that the VaR figure is exceeded will be 2.676% of the value of the portfolio. Hedging with the best performing model, however, reduces the VaR (using OLS) by 79% and the CVaR (using CC) by almost 76% to just 0.631% of the portfolio value. This again demonstrates not only the value of hedging, but also that the use of different performance metrics may differentiate between the best performing model, and therefore the best hedging strategy.

6. Conclusion

This paper compares the hedging effectiveness of some of the commonly applied econometric models using an extensive set of performance metrics for a range of global equity indices.

The metrics chosen are the Variance, Semi-variance, LPM, VaR and CVaR. A number of our results are worth noting. First, we find that the overall dominance of Naïve and OLS hedge strategies is not specific to the use of the variance as a method of evaluating hedging performance. However, the choice of performance method that is used to evaluate an optimal hedge strategy is an important consideration in determining the model that is chosen to generate an optimal hedge ratio. Some performance metrics, especially VaR, yield different results in terms of which econometric model provides the best hedging solution when compared with the traditional variance reduction performance criterion. This result indicates that the measure of hedging effectiveness that is used should also correspond to the outcome that is desired from hedging as different performance metrics may differentiate in terms of model choice.

Second, the performance metrics applied in this paper indicate different hedging performance for short as opposed to long hedgers. This suggests that hedgers who are interested in opposite tails of the return distribution may benefit by considering the use of hedging performance metrics that differentiate between the left and right tail probabilities. This result may be even more pronounced for assets and markets that have strongly asymmetric return distributions, and is currently being investigated.

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Table I: Summary Statistics of Daily Stock Index Futures and Spot Returns[a]

Index	Security	Mean	Std Dev	Skewness	Kurtosis	B-J	LM	Stationarity
American								
S&P500	Spot	-0.008	0.013	0.02	1.83*	182.6*	74.3*	-36.3*
	Futures	-0.008	0.014	0.00	2.13*	247.0*	80.9*	-36.7*
DOW	Spot	0.004	0.013	-0.12	2.79*	427.3*	93.9*	-36.0*
	Futures	0.003	0.014	-0.03	2.55*	355.0*	93.2*	-37.7*
European								
FTSE100	Spot	-0.020	0.013	-0.15*	1.49*	126.7*	220.1*	-35.5*
	Futures	-0.022	0.014	-0.10	1.33*	98.8*	294.6*	-35.9*
CAC40	Spot	0.002	0.017	-0.10	1.63*	147.6*	167.1*	-35.1*
	Futures	0.002	0.017	-0.12*	1.69*	160.2*	140.3*	-34.9*
DAX30	Spot	-0.038	0.018	-0.125	1.62*	147.1*	159.4*	-35.6*
	Futures	-0.030	0.018	-0.12	1.61*	144.6*	167.1*	-35.2*
Asian								
HANGSENG	Spot	-0.011	0.019	0.24*	4.29*	1012.1*	65.2*	-34.4*
	Futures	-0.011	0.021	0.32*	3.11*	550.0*	50.5*	-37.1*
NIKKEI225	Spot	-0.044	0.015	0.11	1.70*	160.8*	42.4*	-37.6*
	Futures	-0.045	0.016	0.18*	1.76*	177.0*	25.8*	-38.5*
95% C.V						5.99	11.07	-2.86

Notes: [a] Summary statistics are presented for the log returns of each spot and futures series. The Bera-Jarque (B-J) statistic combines skewness and kurtosis to measure normality. LM, (with 4 lags) is the Lagrange Multiplier test proposed by Engle (1982). The test statistic for B-J and LM tests are distributed χ^2. Stationarity is tested using the Dickey-Fuller unit root test. *Denotes Significance at the 5% level.

Table II: Evaluation of Hedging Performance

(1)	(2) HE_1 Variance ($x10^{-2}$)	(3) HE_2 Semi-Variance ($x10^{-2}$)	(4) HE_3 LPM ($x10^{-2}$)	(5) HE_4 VaR ($x10^{-2}$)	(6) HE_5 CVaR ($x10^{-2}$)	(7) HE_1 Variance ($x10^{-2}$)	(8) HE_2 Semi-Variance ($x10^{-2}$)	(9) HE_3 LPM ($x10^{-2}$)	(10) HE_4 VaR ($x10^{-2}$)	(11) HE_5 CVaR ($x10^{-2}$)
	Panel A: In-Sample					**Panel B: Out-of-Sample**				
SP500-Short										
Naïve	93.40*	92.65*	97.20*	68.19*	64.78*	**96.95**[a]	**96.28**[a]	**99.32**[a]	78.00*	74.44*
OLS	**93.92**[a]	**93.36**[a]	**97.80**[a]	68.25*	**71.58**[a]	96.32*	95.66*	99.19	**78.96**[a]	75.86*
DVECH	93.63*	92.94*	97.47*	**68.49**[a]	67.11*	96.59*	95.87*	99.26	78.91	76.01
CC	93.73*	93.05*	97.55*	68.16*	67.28*	96.50*	95.87*	99.24	78.72	**76.42**[a]
SP500-Long										
Naïve	93.40*	94.18*	98.67	79.84*	78.35*	**96.95**[a]	**97.47**[a]	**99.61**[a]	75.95	76.71*
OLS	**93.92**[a]	**94.50**[a]	**98.75**[a]	79.69*	78.47*	96.32*	96.84*	99.46	**76.12**[a]	**77.27**[a]
DVECH	93.63*	94.34*	98.71	**80.52**[a]	78.40*	96.59*	96.99*	99.50	75.37*	76.86*
CC	93.73*	94.42*	98.74	80.37*	**78.76**[a]	96.50*	96.99*	99.49	75.66*	77.01
DOW-Short										
Naïve	92.63*	92.19*	96.99*	64.54*	65.12*	**96.96**[a]	**96.52**[a]	**99.38**[a]	**78.76**[a]	**82.97**[a]
OLS	**93.41**[a]	92.93*	97.39	59.91*	68.04	96.10*	95.65*	99.18	76.26*	81.17*
DVECH	93.36	93.03	97.52	**71.64**[a]	**68.30**[a]	96.19*	95.65*	99.20	76.35*	81.38*
CC	93.40	**93.04**[a]	**97.53**[a]	66.89*	68.08	96.29*	95.87*	99.25	76.63*	82.64
DOW-Long										
Naïve	92.63*	93.10*	97.57	74.39*	70.15*	**96.96**[a]	**97.30**[a]	**99.57**[a]	**85.68**[a]	**84.87**[a]
OLS	**93.41**[a]	**93.92**[a]	**98.01**[a]	76.73*	**73.15**[a]	96.10*	96.45*	99.36	81.29*	83.08*
DVECH	93.36	93.71*	97.75	77.03	71.72*	96.19*	96.62*	99.39	81.26*	82.69*
CC	93.40	93.78*	97.80	**77.33**[a]	71.74*	96.29*	96.62*	99.40	81.94*	82.69*
CAC40-Short										
Naïve	87.07*	87.54*	94.05*	61.19*	54.22*	92.44*	92.16*	97.70	71.17*	70.24*
OLS	**88.33**[a]	**88.60**[a]	**94.80**[a]	64.90*	**57.60**[a]	**92.82**[a]	**92.79**[a]	**98.21**[a]	**74.52**[a]	74.43
DVECH	87.86*	88.11*	93.54*	63.96*	55.77*	92.36*	92.25*	97.80	72.13*	70.75*
CC	88.28	88.58	93.89*	**65.91**[a]	56.72*	92.65	92.61*	98.08	73.55*	**74.47**[a]
CAC40-Long										
Naïve	87.07*	86.57*	93.35*	59.55*	53.12*	92.44*	92.73*	**97.94**[a]	72.15*	**71.79**[a]
OLS	**88.33**[a]	**88.05**[a]	**94.41**[a]	**65.76**[a]	**59.27**[a]	**92.82**[a]	**92.89**[a]	97.72	**79.94**[a]	70.69*
DVECH	87.86*	87.59*	93.69*	62.09*	57.31*	92.36*	92.49*	97.63	73.83*	70.06*
CC	88.28	87.97	94.11	64.59*	57.89*	92.65	92.73*	97.86	73.97*	71.11
DAX30-Short										
Naïve	70.12*	72.26*	72.51*	50.28*	40.74*	82.62*	83.55*	94.18*	61.71*	63.29*
OLS	**72.70**[a]	**73.71**[a]	**74.67**[a]	52.52*	**43.77**[a]	**85.97**[a]	87.28*	95.94	66.55*	66.37*
DVECH	71.14*	72.09*	73.22*	51.66*	42.66*	85.84	**88.08**[a]	**96.28**[a]	**70.95**[a]	**68.54**[a]
CC	72.13*	72.96*	74.36	**53.47**[a]	43.62	85.61	87.50*	95.89	68.15*	66.73*
DAX30-Long										
Naïve	70.12*	67.75*	60.20*	44.77*	35.37*	82.62*	82.22*	92.50*	54.69*	58.03*
OLS	**72.70**[a]	**71.58**[a]	70.83	**51.34**[a]	**40.56**[a]	**85.97**[a]	**84.86**[a]	**94.22**[a]	61.68	**61.51**[a]
DVECH	71.14*	70.08*	66.72*	49.96*	39.07*	85.84	83.80*	93.81	**61.93**[a]	60.57
CC	72.13*	71.19*	**70.90**[a]	51.03	40.32	85.61	83.86*	93.78	58.88*	61.31

Table II (Continued)

(1)	(2) HE_1 Variance ($x10^{-2}$)	(3) HE_2 Semi-Variance ($x10^{-2}$)	(4) HE_3 LPM ($x10^{-2}$)	(5) HE_4 VaR ($x10^{-2}$)	(6) HE_5 CVaR ($x10^{-2}$)	(7) HE_1 Variance ($x10^{-2}$)	(8) HE_2 Semi-Variance ($x10^{-2}$)	(9) HE_3 LPM ($x10^{-2}$)	(10) HE_4 VaR ($x10^{-2}$)	(11) HE_5 CVaR ($x10^{-2}$)
	Panel A: In-Sample					**Panel B: Out-of-Sample**				
FTSE-Short										
Naïve	94.60*	94.40*	98.12	73.51*	**71.12**[a]	**97.03**[a]	96.27*	99.24	76.80*	**80.31**[a]
OLS	**94.92**[a]	**94.77**[a]	**98.24**[a]	73.05*	67.72*	96.96	**96.27**[a]	98.93	75.40*	79.24*
DVECH	94.82*	94.74*	96.85*	74.53	68.63*	96.89*	96.27*	**99.26**[a]	**79.25**[a]	79.47*
CC	94.74*	94.70*	97.35*	**74.76**[a]	68.49*	96.75*	95.96*	99.17	77.13*	79.06*
FTSE-Long										
Naïve	94.60*	94.82*	98.40	77.42*	**73.77**[a]	**97.03**[a]	**97.63**[a]	**99.69**[a]	85.54	**86.18**[a]
OLS	**94.92**[a]	**95.09**[a]	**98.45**[a]	75.29*	69.89*	96.96	97.38*	99.15	77.98*	79.45*
DVECH	94.82*	94.91*	97.50*	**77.95**[a]	71.31*	96.89*	97.50*	99.63	**85.63**[a]	84.76*
CC	94.74*	94.79*	97.69*	75.50*	70.00*	96.75*	97.38*	99.62	84.52*	84.47*
HANGSENG - Short										
Naïve	84.44*	84.09*	89.97*	55.33*	49.92*	88.44*	85.71*	95.27*	64.46*	62.29*
OLS	**88.10**[a]	**87.30**[a]	92.19	60.27*	**54.33**[a]	**91.86**[a]	**90.93**[a]	**99.18**[a]	65.06*	71.03
DVECH	87.93*	87.09*	92.29	61.43*	53.32*	91.77	90.25*	97.34*	**68.02**[a]	69.82*
CC	88.00	87.20*	**92.36**[a]	**65.68**[a]	53.79	91.67	90.70*	97.55*	66.13*	**71.04**[a]
HANGSENG - Long										
Naïve	84.44*	84.78*	91.61*	57.46*	54.85*	88.44*	90.42*	97.14*	72.16*	68.22*
OLS	**88.10**[a]	**88.87**[a]	94.72	**67.37**[a]	60.35	**91.86**[a]	92.58*	**99.49**[a]	**76.27**[a]	**75.92**[a]
DVECH	87.93*	88.73*	**95.11**[a]	63.76*	60.36	91.77	**92.74**[a]	98.30*	76.09	75.30
CC	88.00	88.77*	95.00	62.96*	**60.82**[a]	91.67	92.43*	98.21*	75.91	75.81
NIKKEI225 -Short										
Naïve	89.63*	89.60*	96.49*	60.31*	65.78*	90.69*	90.66*	97.53*	73.73*	**80.31**[a]
OLS	**90.17**[a]	**90.20**[a]	**96.79**[a]	**64.43**[a]	**66.86**[a]	91.80*	91.95*	98.06	**75.92**[a]	79.24*
DVECH	89.77*	89.64*	96.34*	61.25*	64.78*	**92.16**[a]	**92.15**[a]	98.15	75.40	79.47*
CC	89.59*	89.48*	96.30*	61.50*	65.00*	92.00*	92.15	**98.17**[a]	75.74	79.06*
NIKKEI225 -Long										
Naïve	89.63*	89.66*	96.08	67.59*	65.28*	90.69*	90.86*	96.66*	66.41*	61.22*
OLS	**90.17**[a]	**90.14**[a]	**96.34**[a]	**69.72**[a]	**66.73**[a]	91.80*	91.68*	97.38	69.90*	69.17*
DVECH	89.77*	89.90*	96.22	69.15*	65.79*	**92.16**[a]	**92.20**[a]	**97.66**[a]	71.45	**71.33**[a]
CC	89.59*	89.70*	96.12	69.23*	65.34*	92.00*	91.99*	97.54	**71.52**[a]	70.43*

Notes: Figures are in percentages. HE_1 – HE_5 give the percentage reduction in the performance measure from the hedged model as compared with a no hedge position. For example, short hedging the S&P500 with the OLS model yields a 93.92% in-sample reduction in the variance as compared with a No-Hedge strategy. The best performing hedging model is highlighted in bold. Statistical comparisons are made for each hedging model against the best performing model. For example, again short hedging the S&P500. If we examine column 1, we can see that the in-sample hedging effectiveness of the Naïve, DVECH and CC models are all significantly different than the best performing OLS model at the 1% level. * Denotes significance at the 1% level.

Table III: Summary of Best Hedging Performance

	Variance	Semi - Variance	LPM	VaR	CVaR
	Panel A: In-Sample				
	Short Hedgers				
	Variance	**Semi - Variance**	**LPM**	**VaR**	**CVaR**
SP500	OLS	OLS	OLS	DVECH	OLS
DOW	OLS	CC	CC	DVECH	DVECH
CAC	OLS	OLS	OLS	CC	OLS
DAX	OLS	OLS	OLS	CC	OLS
FTSE100	OLS	OLS	OLS	CC	NAÏVE
HANGSENG	OLS	OLS	CC	CC	OLS
NIKKEI225	OLS	OLS	OLS	OLS	OLS
	Long Hedgers				
	Variance	**Semi - Variance**	**LPM**	**VaR**	**CVaR**
SP500	OLS	OLS	OLS	DVECH	CC
DOW	OLS	OLS	OLS	CC	OLS
CAC	OLS	OLS	OLS	OLS	OLS
DAX	OLS	OLS	CC	OLS	OLS
FTSE100	OLS	OLS	OLS	DVECH	NAÏVE
HANGSENG	OLS	OLS	DVECH	OLS	CC
NIKKEI225	OLS	OLS	OLS	OLS	OLS
	Panel B: Out-of-Sample				
	Short Hedgers				
	Variance	**Semi - Variance**	**LPM**	**VaR**	**CVaR**
SP500	NAÏVE	NAÏVE	NAÏVE	OLS	CC
DOW	NAÏVE	NAÏVE	NAÏVE	NAIVE	NAÏVE
CAC	OLS	OLS	OLS	OLS	CC
DAX	OLS	DVECH	DVECH	DVECH	DVECH
FTSE100	NAÏVE	OLS	DVECH	DVECH	NAÏVE
HANGSENG	OLS	OLS	OLS	DVECH	CC
NIKKEI225	DVECH	DVECH	CC	OLS	NAÏVE
	Long Hedgers				
	Variance	**Semi - Variance**	**LPM**	**VaR**	**CVaR**
SP500	NAÏVE	NAÏVE	NAÏVE	OLS	OLS
DOW	NAÏVE	NAÏVE	NAÏVE	NAÏVE	NAÏVE
CAC	OLS	OLS	NAÏVE	OLS	NAÏVE
DAX	OLS	OLS	OLS	DVECH	OLS
FTSE100	NAÏVE	NAÏVE	NAÏVE	DVECH	NAÏVE
HANGSENG	OLS	DVECH	OLS	OLS	OLS
NIKKEI225	DVECH	DVECH	DVECH	CC	DVECH

Notes: The findings indicate which models provided the best hedging performance for the different performance measures. For example, for a short hedger holding the S&P500 with VaR as the performance criterion, the best performance out-of-sample would be the OLS model.

Table IV: Out of Sample Comparisons of Hedging Model Performance

(1)	(2) Mean ($x10^{-2}$)	(3) Variance ($x10^{-4}$)	(4) Semi variance ($x10^{-4}$)	(5) LPM 3 ($x10^{-6}$)	(6) VaR ($x10^{-2}$)	(7) CVaR ($x10^{-2}$)
SP500-Short						
None	0.0900	1.1133*	0.4839*	0.8655*	2.082*	2.676*
Naïve	0.0001	0.0341[a]	0.0180[a]	0.0059[a]	0.458	0.684*
OLS	0.0051	0.0411*	0.0206	0.0070	0.438[a]	0.646*
DVECH	0.0031	0.0382*	0.0196	0.0064	0.439	0.642*
CC	0.0053	0.0394*	0.0200	0.0066	0.443	0.631[a]
SP500-Long						
None	-0.0900	1.1133*	0.6317*	1.2385*	1.746*	2.692*
Naïve	-0.0001	0.0341[a]	0.0160[a]	0.0048[a]	0.420	0.627
OLS	-0.0051	0.0411*	0.0204	0.0066*	0.417[a]	0.612[a]
DVECH	-0.0031	0.0382*	0.0185	0.0062	0.430*	0.623
CC	-0.0053	0.0394*	0.0192	0.0063	0.425	0.619
DOW-Short						
None	0.0868	1.0507*	0.4596*	0.7994*	2.161*	3.388*
Naïve	0.0009	0.0325[a]	0.0161[a]	0.0050[a]	0.459[a]	0.577[a]
OLS	0.0068	0.0410*	0.0195	0.0066	0.513*	0.638*
DVECH	0.0063	0.0401*	0.0196	0.0064	0.511*	0.631*
CC	0.0071	0.0392*	0.0189	0.0060	0.505*	0.588*
DOW-Long						
None	-0.0868	1.0507*	0.5919*	1.2029*	2.801*	3.912*
Naïve	-0.0009	0.0325[a]	0.0161[a]	0.0052[a]	0.401[a]	0.592[a]
OLS	-0.0068	0.0410*	0.0213	0.0076	0.524*	0.662
DVECH	-0.0063	0.0401*	0.0204	0.0074	0.525*	0.677*
CC	-0.0071	0.0392*	0.0202	0.0072	0.506*	0.677*
CAC40-Short						
None	0.0575	2.3814*	1.1229*	3.1028*	3.732*	5.108*
Naïve	-0.0005	0.1800*	0.0882	0.0714	1.076*	1.520*
OLS	0.0055	0.1711[a]	0.0815[a]	0.0556[a]	0.951[a]	1.306
DVECH	0.0218	0.1817*	0.0868	0.0682	1.040*	1.494*
CC	0.0184	0.1750	0.0833	0.0596	0.987	1.304[a]
CAC40-Long						
None	-0.0575	2.3814*	1.2515*	4.0931*	4.237*	6.292*
Naïve	0.0005	0.1800*	0.0911	0.0844[a]	1.180*	1.775[a]
OLS	-0.0055	0.1711[a]	0.0889[a]	0.0935	0.850[a]	1.844
DVECH	-0.0218	0.1817*	0.0942	0.0972	1.109*	1.884
CC	-0.0184	0.1750	0.0911	0.0878	1.103*	1.818
DAX30-Short						
None	0.1820	3.0504*	1.3683*	4.2459*	4.179*	5.530*
Naïve	0.0591	0.5295*	0.2255	0.2470	1.600*	2.030
OLS	0.0761	0.4281[a]	0.1735	0.1724	1.398*	1.860
DVECH	0.0967	0.4315	0.1632[a]	0.1579[a]	1.214[a]	1.740[a]
CC	0.0932	0.4394	0.1715	0.1744	1.331*	1.840
DAX30-Long						
None	-0.1820	3.0504*	1.7036*	5.3862*	4.502*	6.267*
Naïve	-0.0591	0.5295*	0.3031	0.4039	2.040*	2.630
OLS	-0.0761	0.4281[a]	0.2581[a]	0.3114[a]	1.725	2.412[a]
DVECH	-0.0967	0.4315	0.2761	0.3332	1.714[a]	2.471
CC	-0.0932	0.4394	0.2747	0.3349	1.851*	2.425

Table IV (Continued)

(1)	(2) Mean ($x10^{-2}$)	(3) Variance ($x10^{-4}$)	(4) Semi variance ($x10^{-4}$)	(5) LPM 3 ($x10^{-6}$)	(6) VaR ($x10^{-2}$)	(7) CVaR ($x10^{-2}$)
FTSE100-Short						
None	0.0491	1.4466*	0.6431*	1.5173*	2.728*	4.418*
Naïve	-0.0019	0.0431 [a]	0.0242	0.0115	0.633*	0.870 [a]
OLS	0.0002	0.0444	0.0237 [a]	0.0162	0.671*	0.917*
DVECH	0.0161	0.0450	0.0244	0.0112 [a]	0.566 [a]	0.907*
CC	0.0141	0.0469*	0.0261	0.0126	0.624*	0.925*
FTSE100-Long						
None	-0.0491	1.4466*	0.8013*	2.1440*	3.243*	4.828*
Naïve	0.0019	0.0431 [a]	0.0188 [a]	0.0066 [a]	0.469	0.667 [a]
OLS	-0.0002	0.0444	0.0206	0.0181	0.714	0.992
DVECH	-0.0161	0.0450	0.0204	0.0080	0.466 [a]	0.736
CC	-0.0141	0.0469	0.0206	0.0081	0.502	0.750
HANGSENG-Short						
None	0.1150	1.0807*	0.4410*	0.8552*	2.164*	3.519*
Naïve	-0.0032	0.1253*	0.0626	0.0404	0.769	1.327*
OLS	0.0180	0.0885 [a]	0.0403 [a]	0.0070 [a]	0.756	1.019
DVECH	0.0101	0.0895	0.0427	0.0228	0.692 [a]	1.062
CC	0.0162	0.0896	0.0409	0.0209	0.733	1.019 [a]
HANGSENG-Long						
None	-0.1150	1.0807*	0.6465*	1.3006*	2.777*	3.704*
Naïve	0.0032	0.1253*	0.0617	0.0371	0.773*	1.177
OLS	-0.0180	0.0885 [a]	0.0481 [a]	0.0066 [a]	0.659 [a]	0.892 [a]
DVECH	-0.0101	0.0895	0.0466	0.0221	0.664	0.915
CC	-0.0162	0.0896	0.0486	0.0233	0.669	0.896
NIKKEI225-Short						
None	0.0841	1.9760*	1.0060*	2.8766*	3.784*	4.418*
Naïve	-0.0039	0.1837*	0.0941	0.0711	0.994*	0.870 [a]
OLS	0.0027	0.1623*	0.0808	0.0559	0.911 [a]	0.917*
DVECH	0.0009	0.1555 [a]	0.0789 [a]	0.0531	0.931	0.907*
CC	0.0014	0.1577	0.0792	0.0527 [a]	0.918	0.925*
NIKKEI225-Long						
None	-0.0841	1.9760*	0.9738*	1.9145*	2.953*	3.669*
Naïve	0.0039	0.1837*	0.0889	0.0639	0.992*	1.423*
OLS	-0.0027	0.1623*	0.0808	0.0501	0.889*	1.131
DVECH	-0.0009	0.1555 [a]	0.0760 [a]	0.0449 [a]	0.843	1.052 [a]
CC	-0.0014	0.1577	0.0779	0.0472	0.841 [a]	1.085

Notes: This table presents Out-of-Sample hedge portfolio statistics which form the basis of our performance measures. Taking the short hedged S&P500 for example, the unhedged portfolio yields a VaR of 2.082%. Comparisons are made between models using t-statistics obtained from a bootstrap resampling procedure. [a] denotes the minimum risk measure. * denotes significance at the 1% level

Footnotes

1. The same applies to each of the performance metrics we employ.
2. We calculated LPM for three different orders of LPM corresponding to n=1, n=2 and n=3 however in common with Lien and Demirer (2003) we found similar performance levels and therefore focus only on the case n=3 which is appropriate from a hedging perspective.
3. Further details are available on request.
4. Obviously the variance will not distinguish between opposite tails of the return distribution and therefore will yield the same results for long and short hedgers.