Hedge ratio estimation and hedging effectiveness: the case of the S&P 500 stock index futures contract[a]

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Abstract: This paper investigates the hedging effectiveness of the Standard & Poor's (S&P) 500 stock index futures contract using weekly settlement prices for the period July 3rd, 1992 to June 30th, 2002. Particularly, it focuses on three areas of interest: the determination of the appropriate model for estimating a hedge ratio that minimizes the variance of returns; the hedging effectiveness and the stability of optimal hedge ratios through time; an in-sample forecasting analysis in order to examine the hedging performance of different econometric methods. The hedging performance of this contract is examined considering alternative methods, both constant and time-varying, for computing more effective hedge ratios. The results suggest the optimal hedge ratio that incorporates nonstationarity, long run equilibrium relationship and short run dynamics is reliable and useful for hedgers. Comparisons of the hedging effectiveness and in-sample hedging performance of each model imply that the error correction model (ECM) is superior to the other models employed in terms of risk reduction. Finally, the results for testing the stability of the optimal hedge ratio obtained from the ECM suggest that it remains stable over time.

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1 Introduction

The hedging effectiveness of stock index futures has been extensively investigated in recent years using the portfolio approach to hedging and the associated minimum variance hedge ratio of Johnson (1960). Hedging through trading futures is a process used to control or reduce the risk of adverse price movements. The introduction of stock index futures contracts offered to market participants the opportunity to manage the market risk of their portfolios without changing the portfolios composition.

The effectiveness of a hedge becomes relevant only in the event there is a significant change in the value of the hedged item. A hedge is effective if the price movements of the hedged item and the hedging derivative roughly offset each other. According to Pennings and Meulenberg (1997), a determinant in explaining the success of financial futures contracts is the hedging effectiveness of futures contracts.

All previous studies, which investigate measures of hedging effectiveness, use the simple Ordinary Least Squares Regression (OLS) for estimating hedge ratios. However, there is wide evidence that the simple regression model is inappropriate to estimate hedge ratios since it suffers from the problem of serial correlation in the OLS residuals and the heteroskedasticity often encountered in cash and futures price series (e.g., Herbst et al., 1993). So, to counter the problem of inconstant variances of index futures and stock index prices, a number of papers measure optimal hedge ratios via autoregressive conditional heteroskedastic processes which allow for the conditional variances of spot and futures prices to vary over time (e.g., Park and Switzer, 1995b).

A second problem encountered when estimating hedge ratios arises from the cointegrative nature between spot and futures markets. If no account is made for the presence of cointegration it can lead to an under-hedged position due to the mis-specification of the pricing behaviour between these markets (Ghosh, 1993).

Numerous studies have used error correction models when analyzing the spot-futures relationship (e.g., Chou et al., 1996), while other papers have also included both error-correction terms and a time-varying risk structure (e.g., Lien and Tse, 1999).

This paper contributes to the existing literature in a number of ways. First, the chosen period updates earlier work on the S&P 500 stock index futures contract that has not considered periods of the late 1990s and early 2000s. Second, different model specifications, both constant and time-varying, are estimated and compared so as to arrive at the most appropriate model, which takes account the univariate properties of cash and futures prices. Third, the minimum variance hedge ratios (MVHRs) are estimated via alternative methods, already used in previous studies (OLS, ECM, GARCH model, and ECM with GARCH error structure), but also the EGARCH model. This model has never been considered for computing hedging ratios in prior empirical studies known. Finally, an in-sample forecasting analysis is conducted in order to examine the hedging performance of alternative models, while the stability of the optimal hedge ratio through time for the superior model is also examined, given that investors are likely to use hedge ratios estimated in one period to hedge positions in the coming period.

The rest of the paper is organized as follows. The next section briefly discusses theoretical considerations by presenting the traditional one-to-one, the beta, and the minimum variance hedging strategies. The third section briefly reviews the relevant empirical research. The data and methodology adopted are then set out. Finally, results are presented and are followed by concluding remarks.

2 Theoretical considerations

In considering the use of futures contracts to hedge an established spot position the investor must decide on the hedge ratio, h, to be employed. The hedge ratio is the ratio of the number of units traded in the futures market to the number of units traded in the spot market. The particular hedging strategy adopted depends crucially on the investor's objectives. Research has concentrated on three hedging strategies: the traditional one-to-one; the beta hedge; and the minimum variance hedge proposed by Johnson (1960) and also associated with Ederington (1979).

The traditional strategy emphasizes the potential for futures contracts to be used to reduce risk. It is a very simple strategy, involving the hedger in taking up a futures position that is equal in magnitude, but opposite in sign to the spot market position, i.e. h = -1. If proportionate price changes in the spot market match exactly those in the futures market the price risk will be eliminated. However, in practice, it is unlikely for a perfect correlation between spot and future returns to exist, and hence the hedge ratio that minimizes the variance of returns will definitely differ from –1.

Beta hedge ratio simply refers to the portfolio's beta. The beta hedge has the same objective as the traditional 1:1 hedge that establishes a futures position that is equal in size but opposite in sign to the spot position. Yet, when the cash position is a stock portfolio, the number of futures contracts needed for full hedge coverage needs to be adjusted by the portfolio's beta. In many cases the portfolio to be hedged will be a subset of the portfolio underlying the futures contract, and hence the beta hedge ratio will deviate from –1. However, it may be the case that the futures contract may mirror the portfolio to be hedged, and thus the beta hedge ratio will be the same as the traditional hedge ratio.

Johnson (1960) proposed the minimum variance hedge ratio (MVHR) as an alternative to the classic hedge. He applied modern portfolio theory to the hedging problem. It was the first time that definitions of risk and return in terms of mean and variance of return were employed to this problem. Johnson maintained the traditional objective of risk minimization as the main goal of hedging but defined risk as the variance of return on a two-asset hedged portfolio. The MVHR (h*) is measured as follows:

$$h^* = -\frac{X_f}{X_S} = \frac{\sigma_{SF}}{\sigma_F^2} \qquad (1)$$

where, X_F^* and X_S represent the relative dollar amount invested in futures and spot respectively, σ_{SF} is the covariance of spot and futures prices changes, and σ^2_F is the variance of futures price changes. It should be mentioned that the minimum variance hedge is the coefficient of the regression of spot price changes on futures price changes. The negative sign reflects the fact that in order to hedge a long stock position it is necessary to go short (i.e. sell) on futures contracts. Using the MVHR assumes that investors are infinitely risk averse. While such an assumption about risk-return trade-off is unrealistic, the MVHR provides an unambiguous benchmark against which to assess hedging performance (Butterworth and Holmes, 2001)

Johnson also developed a measure of the hedging effectiveness (E) of the hedged position in terms of the reduction in variance of the hedge [VAR (H)] over the variance of the unhedged position [VAR (U)]:

$$E = 1 - \frac{VAR(H)}{VAR(U)} \qquad (2)$$

substituting the minimum variance X_f^*, and rearranging yields:

$$E = 1 - \frac{X_S^2 \sigma_{\Delta S}^2 \left(1 - \rho^2\right)}{X_S^2 \sigma_{\Delta S}^2} = \rho^2 \qquad (3)$$

where, the ρ^2 is the squared simple correlation coefficient of spot, futures price changes. The measure of hedging effectiveness for the MVHR Model is the squared simple correlation coefficient of spot price changes (ΔS) to futures price changes (ΔF), or the R^2 of a regression of spot price change on futures price change[1].

3 Literature review

The majority of the studies investigating the hedging on stock index futures relates to the USA, although more recent research has been focused on UK, Japan and Germany. In the first analysis of hedging effectiveness of stock index futures, Figlewski (1984) calculated the risk and returns combinations of different capitalization portfolios underlying five major stock indices that could have been achieved by using the S&P 500 stock index futures as a hedging instrument for the period June 1982 to September 1983. The risk minimizing hedge ratios were estimated by OLS on historical spot and futures returns. He found that for all indices represented diversified portfolios ex post MVHRs were better than the beta hedge ratios. With large capitalization portfolios, risk was considerably reduced in contrast to smaller stocks portfolios. Moreover, Figlewski pointed out that dividend risk was not an important factor, whereas time to maturity and hedge duration were.

Junkus and Lee (1985) investigated the hedging effectiveness of three U.S stock index futures under alternative hedging strategies. The optimal hedge ratios were calculated using the OLS conventional regression model. Their results indicated the superiority of MVHR. Moreover, there was little evidence about the impact of contract expiration and hedging effectiveness. Ghosh (1993) extended studies of lead and lag relationships between stock index and stock index futures prices by using an ECM, arguing that the standard OLS approach is not well specified in estimating hedge ratios ratio (for the S&P 500, NYSE composite index, but not the DJIA index) because it ignores lagged values.

Holmes (1996) tried to assess the appropriate econometric technique when estimating optimal hedge ratios of the FTSE-100 stock index by applying a GARCH (1,1) as well. He showed that in terms of risk reduction a hedge strategy based on MVHRs estimated using OLS outperforms optimal hedge ratios that are estimated using more advanced econometric techniques such as an error correction model or a GARCH (1,1) approach. Furthermore, he provided evidence that effectiveness increased with hedge duration, while the impact of an expiration effect was not straightforward.

Butterworth and Holmes (2001) investigated the hedging effectiveness of the FTSE-Mid 250 stock index futures contract using actual diversified portfolios in the form of Investment Trust Companies (ITCs). Using an alternative econometric technique (Least Trimmed Squares Approach) to estimate hedge ratios, their results showed that this contract is superior to the FTSE-100 index futures contact when hedging cash portfolios mirroring the Mid250 and the FT Investment Trust (FTIT) indices

Chou, Denis and Lee (1996) estimated and compared the hedge ratios of the conventional and the error correction model using Japan's Nikkei Stock Average (NSA) index and the NSA index futures with different time intervals for the period 1989- 1993. Examining an out-of-sample performance, the error correction model outperformed the conventional approach, while the opposite hold by evaluating the in-sample portfolio variance. As far as temporal aggregation is concerned, their results showed that hedging effectiveness increased as hedge duration increased. Finally, Lypny and Powalla (1998) examined the hedging effectiveness of the German stock index DAX futures and showed that the application of a dynamic hedging strategy based on a GARCH (1,1) process is economically and statistically the most effective model.

4 Methodology

This paper aims to determine the appropriate model when estimating optimal hedge ratios. The alternative models employed are the following:

Model 1: The Conventional Regression Model

This model is just a linear regression of change in spot prices on changes in futures prices. Let S_t and F_t be logged spot and futures prices respectively, the one period MVHR can be estimated as follows:

$$\Delta S_t = a_0 + \beta \cdot \Delta F_t + u_t \qquad (4)$$

where u_t is the error from the OLS estimation, ΔS_t and ΔF_t represent spot and futures price changes and the slope coefficient β is the optimal hedge ratio (h*).

Model 2: The Error Correction Model

Engle and Granger (1987) stated that if sets of series are cointegrated, then there exists a valid Error Correction Representation of the data. Thus, if S_t represents the index spot price series and F_t the index of futures price series and if both series are I (1), there exists an error correction representation of the following form:

$$\Delta S_t = au_{t-1} + \beta \cdot \Delta F_t + \sum_{k=1}^{m} \theta \cdot \Delta F_{t-k} + \sum_{j=1}^{n} \phi \cdot \Delta S_{t-j} + e_t \qquad (5)$$

where $u_{t-1} = S_{t-1} - [a_0 + a_1 F_{t-1}]$ is the error correction term and has no moving average part; the systematic dynamics are kept as simple as possible and enough lagged variables are included in order to ensure that e_t is a white noise process; and the coefficient β is the optimal hedge ratio[2].

Model 3: The GARCH Model

A useful generalization of ARCH models introduced by Bollerslev (1986) is the GARCH (1,1) model, that parameterizes volatility as a function of unexpected information shocks to the market. The equation for GARCH (1,1) is the following:

$$\sigma_t^2 = a_0 + a_1 \cdot e_{t-1}^2 + \beta \cdot \sigma_{t-1}^2 \qquad (6)$$

The equation specified above is a function of three terms: the mean α_0, news about volatility from the previous period, measured as the lag of the squared residual from the mean equation e^2_{t-1} (the ARCH term), and last period's forecast variance σ^2_{t-1} (the GARCH term). The more general GARCH (p, q) calculates σ_t^2 from the most recent p observations on e^2 and the most recent q estimates of the variance rate.

Estimation sometimes results in: $a_1 + \beta \approx 1$, or even $\alpha_1 + \beta > 1$. Values of $\alpha_1 + \beta$ close to unity imply that the persistence in volatility is high. In other words, in order to interpret expression (6), suppose that there is a large positive shock e_{t-1}, and hence e^2_{t-1} is large, then the conditional variance σ_t^2 increases. This shock is permanently "remembered" if $\alpha_1 + \beta$ is greater or equal to unity but dies out if it is less than unity.

Model 4: The EGARCH Model

The EGARCH model is given by:

$$\log \sigma_\tau^2 = \varpi + \beta \cdot \log(\sigma_{t-1}^2) + \gamma\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + a\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \qquad (7)$$

where ϖ , α, β, γ are constant parameters (Nelson, 1991). The left-hand side is that of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. Since, the level $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is included, the model will be asymmetric if $\gamma \neq 0$. The presence of leverage effects can be tested by the hypothesis that $\gamma > 0$. If the leverage effect term, γ, after running the appropriate regression, is negative and statistically different from zero, this will imply that positive shocks generate less volatility than negative shocks (bad news).

Comparisons are then made of the hedging effectiveness associated with each hedging strategy based on the minimum variance hedge ratio estimations, using the simple OLS, the ECM, the ECM with GARCH errors and the GARCH and EGARCH models. The question of the appropriate model to use when estimating the optimal hedge ratio of the S&P 500 index futures contracts traded in the US is of considerable interest to investors wishing to use this contract for hedging.

In addition, comparisons of in-sample hedging performance between the four models are given. Investors are usually concerned with how well they have done in the past. Therefore, the in-sample hedging performance is a sufficient way to evaluate the hedging performance of alternative models employed to obtain the optimal hedge ratio. The measures that are most used to identify how well individual variables track their corresponding series are the Root Mean Square Errors (RMSEs), Mean Absolute Errors (MAEs) and Mean Absolute Percent Errors (MAPEs).

Finally, the issue of the stability of the estimated hedge ratio is also examined in this study using the Chow's breakpoint test for the superior model. We apply the Chow's breakpoint test by examining parameter consistency from 19/3/1999 onwards. The particular date is chosen for the following reasons. First of all, the date should be within our sample, and also because, after plotting both our series, we identified a peak in the residuals at that particular date.

5 Data and empirical results

5.1 Data

In this paper the hedging performance of the S&P 500 futures contract is examined using data relating to the period July 1992 to June 2002. The spot portfolio to be hedged is that underlying the S&P 500 index. The data used for both spots and futures relate to closing prices on a weekly basis. Weekly data are preferred in this study for several reasons. First, the choice of weekly hedges is realistic and implies that hedgers in the market rebalance their futures positions on a weekly basis. Second, the one-week hedge can be used to reduce risk without incurring excessive transactions costs. Finally, the weekly hedging horizon is the most common choice of the prior empirical studies in several derivatives markets. In all estimations the futures contract nearest to expiration is used. In line with previous studies changes in logarithms of both spot and futures price are analyzed, and no adjustment is made for dividends. All prices were obtained from DataStream.

5.2 Tests of units roots and cointegration

Tests for the presence of a unit root are performed by conducting the Augmented Dickey-Fuller and Phillips-Perron unit root tests under the assumption that there is no linear trend in the data generation process. However, after plotting the data we identified that both our series appear to be trended. Therefore, the tests were performed using a linear time trend and an intercept. The ADF (4 lags) and PP (5 lags) test statistics indicate that none of the level series are stationary processes; while for the differenced series the hypothesis of a unit root is rejected at 5% level, suggesting that the differenced series are stationary processes. The test results are reported in Table 1.

Since we have identified that both our series, the spot prices (S_t) and future prices (F_t), are I(1), then the presence or absence of cointegration can be investigated by simply regressing the value of the spot asset (S_t) on the value of the futures contract (F_t). In particular a test for a unit root in the estimated residuals will determine the presence or absence of cointegration. The estimates of a_0 and a_1 of the long run regression are presented in equation (8). Table 2 provides the ADF and PP tests on the residuals.

$$S_t = 0.027309 + 0.994311 \cdot F_t + u_t \quad (8)$$

The results suggest that the spot S&P 500 index is cointegrated with the S&P 500 index futures, since it shows that the error term is I(0). Evidence in favour of a cointegrated system between weekly closing prices on the stock index and weekly 'settlement' prices on the stock index futures implies that both the cash and the futures markets have a tendency to move together in the long run, in spite of the fact that short run deviations from equilibrium may be observed due to temporary dissequilibrium forces.

In addition, we notice that the coefficient of F_t is very close to unity. Even though other time intervals (hedge duration) are not examined in this paper, our finding corresponds to previous studies that support there is a tendency for the magnitude of the hedge ratio to increase with the level of aggregation, suggesting that the length of the time interval has an important impact on the hedge ratios (e.g., Figlewski, 1984; Chou et al., 1996).

5.3 The results from Model 1, 2, 3 and 4

The optimal hedge ratio from the regression of the form given in equation (4), i.e. using the "Conventional Approach", is presented in the following equation:

$$\Delta S_t = 0.000178 + 0.947281 \cdot \Delta F_t + u_t \quad (9)$$

The slope coefficient β is the optimal hedge ratio. In our case it is close to unity and highly significant. The adjusted R^2 is 0.975164 and indicates a good fit. However, the model exhibits serial correlation and heteroskedasticity, while there are no ARCH (1) effects.

Since the spot S&P 500 index is cointegrated with the S&P 500 index futures, then, according to Engle and Granger (1987), an ECM must exist as presented in equation (5). Table 3 presents a summary of the ECM that was chosen according to the smallest value of the Akaike Information criterion (AIC) and the Schwarz's Bayesian information criterion (BIC). Any insignificant variables are excluded from the model to reach a more parsimonious specification. By examining Table 3, we can report that the optimal hedge ratio is 0.95582 and the error correction model including no lags has a nice fit ($\overline{R}^2 = 0.98134$). In addition, this model has a small standard error of regression, while the error correction coefficient (u_{t-1}) is statistically significant at 5% level. The coefficient of the error term measures the single period response of the Left Hand Side variable (ΔS_t) to departures from equilibrium and has important predictive powers. Indeed, it could be mentioned that about 50% of the discrepancy between S_t and its long run equilibrium is corrected within a week. This shows that last period's dissequilibrium error has a great impact in the adjustment process of the subsequent price changes in the cash market. It is also noticeable that the intercept is highly insignificant indicating there is no linear time trend in the data generating process.

The diagnostics tests indicate no serial correlation up to the second lag, no ARCH (1) effects, but the problem of heteroskedasticity is observed. The adjusted R^2 indicates that 98% of the variance is explained by our model. However, the presence of heteroskedasticity, violating one of the assumptions underlying OLS, leads us to re-estimate the optimal hedge ratio using two appropriate methods: GARCH and EGARCH models. In addition, an ECM with GARCH errors was also examined. This was done in order to correct for the presence of heteroskedasticity.

Table 4 presents the results from the GARCH model, the EGARCH model and the ECM with GARCH errors employed in this paper. First, we fitted a GARCH (1,1) and a GARCH (2,1) model. The GARCH parameter β corresponding to equation (6) is significant for both of our models, while the ARCH parameter a_1 is highly insignificant in the case of a GARCH (2,1). Since a_1 and a_2 are insignificant at the 5% level, this indicates that old shocks have no impact on current volatility, hence heteroskedasticity is corrected. We obtain an optimal hedge ratio of 0.944651 very close to unity. The adjusted R^2 is 0.974120 indicating a nice fit. On the other hand, the ARCH (1) term for the GARCH (1,1) is highly significant at the 5% level. Testing for ARCH (1) effects we obtain a p-value of 0.284243 and hence heteroskedasticity is corrected (we do not reject the null hypothesis of no ARCH effects at the 5% level). However, the sum of the ARCH and GARCH coefficients ($a_1 + \beta$) is 0.730494 (see equation 6) indicating that old shocks have an impact on current volatility but this effect is not permanently remembered. Instead, due to the fact that this sum is less than unity it dies out.

In addition an EGARCH (1,1) model was estimated where all terms were statistically significant. The leverage effect term γ is positive and statistically different from zero, indicating the existence of the leverage effect (evidence of asymmetry)[3]. Hence, negative shocks generate less volatility than positive shocks (good news). We obtain an optimal hedge ratio of 0.957953, very close to unity. The adjusted R^2 is 0.971802 indicating a nice fit.

Finally, we examined an ECM with GARCH errors, in order to correct for heteroskedasticity. In particular, we fitted a GARCH (1,1), a GARCH (1,0), and a GARCH (2,0) upon our ECM. The GARCH (2,0) model manages to correct heteroskedasticity. Testing for ARCH (1) effects we obtain a p-value of 0.510821 and hence heteroskedasticity is corrected. Both ARCH terms are highly significant at 5% level; while the two alternative models manage to explain the behavior of the dependent variable (insignificant ARCH terms). Thus, we consider the GARCH (1,0) model quite better than the GARCH (1,1) since we obtain a higher adjusted R^2 and it has the smallest standard error of regression. The optimal hedge ratio we obtain of such an approach is 0.956218, very close to unity. We should mention here that although the ECM with GARCH (1,0) errors performs statistically better than the simple error correction representation, it did not manage to increase hedging effectiveness, as measured by using the adjusted R^2, and hence the simple error correction representation is considered superior.

Table 5 summarizes the comparisons of the optimal hedge ratios estimated using alternative methods. In terms of risk reduction, the appropriate method for estimating optimal hedge ratios is the ECM. The results from the other models did not manage to increase hedging effectiveness, as measured by the adjusted R^2, and hence the simple error correction representation is considered superior.

5.4 In-sample analysis

Table 5 reports also the RMSEs, MAEs and MAPEs for each model. The results indicate that the error-correction specification outperforms all the other models since it has the smallest values of the above measures. However, all models performed well since the estimated RMSEs are close to zero. Therefore, we could claim that the ECM fits the available data sufficiently well and can forecast adequately.

On average, the ECM gives forecasts with about 12% reduction in RMSEs. In contrast, Park and Switzer (1995b) find that the hedge strategy for the S&P 500, MMI and Toronto 35 index futures using the GARCH is superior to other methods. Chou et al. (1996) report that the OLS outperforms the ECM for the Nikkei futures index. However, they report that for out-of-sample forecasts the reverse stands. Moreover, Lypny and Powalla (1998) provide evidence that a GARCH (1,1) is economically and statistically superior to other models based on the RMSEs, while Holmes (1996) finds that the OLS hedges dominate.

Finally, the issue of the stability of the estimated hedge ratio is also examined using Chow's breakpoint test for the ECM, which was shown to be the superior model. We apply Chow's breakpoint test by examining parameter consistency from 19/3/1999 onwards. The results from Table 6 indicate that null hypothesis of no breakpoint is not rejected since the probability value of 0.174494 is greater than 0.05 (5%).

6 Conclusions

This paper estimated optimal hedge ratios and examined the hedging effectiveness of the S&P 500 index using alternative models, both constant and time-varying, over the period from July 1992 to June 2000. The findings of this study suggest that in terms of risk reduction the error correction model is the appropriate method for estimating optimal hedge ratios since provides better results than the conventional OLS method, the ECM with GARCH errors, the GARCH model, and the EGARCH (1,1) model.

The adjusted R^2 value, which measures the effectiveness of the hedge, is higher for the error correction model. In addition, judging from the in-sample test the proposed error correction specification achieves a significantly lower RMSE when compared with forecasting performance of the alternative models. Indeed, in sample analysis indicates that on average, the ECM provides better forecasts with about 12% reduction in RMSEs. Finally, the issue of the stability of the estimated hedge ratio was also examined in this study using the Chow's Breakpoint test for the error-correction model, which was shown to be the superior model. The results indicated reasonable parameter consistency.

The evidence presented in this paper strongly suggests that the S&P 500 stock index futures contract is an effective tool for hedging risk. This is consistent to earlier studies on S&P 500 index covering the 1980s and early 1990s. Hence, the introduction of this contract has given portfolio managers and investors a valuable financial instrument by which they can avoid risk at times they wish to do this without liquidating their spot position or changing their portfolios composition.

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Footnotes

[1] Other studies have incorporated expected returns into hedging decisions and developed risk-return measures of hedging effectiveness (e.g., Howard and D'Antonio, 1984). However, such models display the same shortcoming as Johnson's MVHR in that they require a subjective assumption to be made in relation to investors' preferences.

[2] The ECM with GARCH error structure also used in this paper meets the earlier criticisms of possible model misspecifications and time-varying hedge ratios, since the Error-Correction Term (ECT) describes the long-run relationship between spot and futures prices and the GARCH error structure permits the second moments of their distributions to change over time.

[3] Notice that using the Threshold Autoregressive Conditional Heteroskedasticity (TARCH) (1,1) model, the results do not indicate any evidence of asymmetry. The results are available from the authors upon request.

Table 1 ADF and PP tests for unit root

Interval	*S&P 500 (Levels)*				*S&P 500 (Differences)*			
	Spot		Futures		Spot		Futures	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
1 week	-2.5539	-2.5403	-2.5769	-2.6103	-10.4302*	-24.8812*	-10.7417*	-25.4163*
Critical Value	-3.4422							

The null hypothesis is that series has a unit root.
*Denotes that the test statistics are significantly different from zero at the 5% level.

Table 2 ADF and PP tests for unit root on the residuals

ADF		PP
-8.9677*		-11.9916*
Critical Value	-3.4422	

*Denotes that the null hypothesis of no cointegration is rejected at the 5% level.

Table 3 Results from the Error Correction Model

Variable	Coefficient	Std. Error	t-Stat	Prob.
C	0.000138	0.000127	0.882026	0.3923
u_{t-1}	-0.4983901	0.0386350	-11.842860	0.00000
ΔF_t^*	0.955820	0.005358	146.3982	0.00000

LAG CRITERIA

Akaike info criterion	-8.898341
Schwarz criterion	-8.854448

MODEL ADEQUACY

Standard Error of Regression	0.002501
Mean	0.003316
Adjusted R-squared	0.981341
	Prob.
Serial Correlation LM Test	0.574682
ARCH LM Test	0.188212
White Heteroskedasticity Test	0.000000

Notes: The dependent variable of the ECM is defined as $\Delta S_t = \text{Log}(S_t/S_{t-1})$, while $\Delta F_t = \text{Log}(F_t/F_{t-1})$.

[*] The Optimal Hedge Ratios (h^*) is the coefficient of the variable ΔF_t.

Serial Correlation LM Test is Breusch-Godfrey's Lagrange Multiplier (LM) Statistic for second and fifth serial correlation in the residuals, being asymptotically distributed as X^2 under the null of serial independence.

The ARCH LM Test is Engle's Lagrange Multiplier (LM) Statistic for Autoregressive Conditional Heteroskedasticity under the null of no ARCH effect.

Heteroskedasticity Test is White's test statistic for heteroskedasticity in the residuals, being asymptotically distributed as X^2 under the null of no heteroskedasticity.

Table 4 Results from the GARCH model, the EGARCH model and the ECM with GARCH errors

GARCH (1,1)

Variable	Coefficient	Std. Error	z-Stat	Prob.
ΔF_t^*	0.948062	0.005590	163.8893	0.0000
α_1 (ARCH (1))	0.150432	0.058057	2.635951	0.0078
β (GARCH (1))	0.580062	0.150959	3.793963	0.0000

Adjusted R-squared= 0.973843 S.E of regression= 0.003298 ARCH test (p- value)= 0.284243

GARCH (2,1)

Variable	Coefficient	Std. Error	z-Stat	Prob.
ΔF_t^*	0.944651	0.006241	156.2389	0.0000
α_1 (ARCH (1))	0.091077	0.066378	1.396932	0.1567
α_2 (ARCH (2))	0.090981	0.087799	1.041368	0.2882
β (GARCH (1))	0.605277	0.148270	4.096276	0.0000

Adjusted R-squared= 0.974120 S.E of regression= 0.003382 ARCH test (p- value)= 0.467912

EGARCH (1,1)

Variable	Coefficient	Std. Error	z-Stat	Prob.
ΔF_t^*	0.957953	0.007228	136.8890	0.0000
γ	0.230686	0.040590	5.078608	0.0000
EGARCH (1)	0.983622	0.005992	143.0483	0.0000

Adjusted R-squared= 0.971802 S.E of regression= 0.003374 ARCH test (p value)= 0.758862

ECM with GARCH (1,1) errors

Variable	Coefficient	Std. Error	z-Stat	Prob.
ΔF_t^*	0.952578	0.005609	169.9308	0.0000
ARCH (1)	0.036582	0.017964	1.944276	0.0582
GARCH (1)	0.968236	0.019892	48.66820	0.0000

Adjusted R-squared= 0.980582 S.E of regression= 0.002812 ARCH test (p- value)= 0.938502

ECM with GARCH (1,0) errors

Variable	Coefficient	Std. Error	z-Stat	Prob.
ΔF_t^*	0.956217	0.005312	183.3577	0.0000
ARCH (1)	0.085387	0.046652	1.710992	0.0928

Adjusted R-squared= 0.980611 S.E of regression= 0.002809 ARCH test (p- value)= 0.963948

ECM with GARCH (2,0) errors

Variable	Coefficient	Std. Error	z-Stat	Prob.
ΔF_t^*	0.956903	0.005293	189.8967	0.0000
ARCH (1)	0.136602	0.061309	2.476901	0.0181
ARCH (2)	0.128350	0.049683	2.693601	0.0084

Adjusted R-squared= 0.980578 S.E of regression= 0.002829 ARCH test (p- value)= 0.510821

* The coefficient of the variable ΔF_t defined as Log (F_t/F_{t-1}) is the Optimal Hedge Ratios (h^*).

Table 5 Comparisons between hedging models

	OLS	ECM	GARCH (2,1)	EGARCH (1,1)
Hedge Ratios	0.947281*	0.955820*	0.944651*	0.957953*
Adjusted R-Squared	0.975164	0.981341	0.974120	0.971802
Serial Correlation (2 Lags) (p-value)	0.00000	0.574682*	-	-
ARCH (1) (p-value)	0.56277*	0.188212*	0.467912*	0.758862*
Heteroskedasticity (p-value)	0.00108	0.000000	-	-
Root Mean Squared Errors (RMSEs) * *	0.004762	0.004183***	0.004771	0.004756
Mean Absolute Error (MAEs) * *	0.003753	0.003194***	0.003798	0.003613
Mean Absolute Percent Error (MAPEs)* *	26.08845	19.16262***	26.22565	26.03724

* Significant at 5% level .

According to the RMSEs, MAEs and MAPEs, the smaller the error, the better the forecasting ability of the model.

** Indicates the smaller error between the models.

Table 6 Stability Test using Chow Breakpoint Test: 19/3/1999

F-statistic	1.264100	Probability	0.174494*
Log likelihood ratio	37.58262	Probability	0.084696

* Denotes that the null hypothesis of no structural change is not rejected at the 5% level.