The hedging effectiveness of stock index futures using KOSPI 200 futures

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ABSTRACT

This paper investigates the hedging effectiveness of stock index futures using KOSPI 200 futures in Korea during the period 1996. 5. 3 to 2005. 12. 29. The hedge ratios are estimated by vech model, asymmetric vech model, CCOR model, asymmetric CCOR model, BEKK model, and asymmetric BEKK model and the hedging performances calculated by these models are compared. Main findings are as follows. First, two prices are non-stationary. However, two return series are all stationary. There is a cointegration relationship between two level prices. Second, for in-sample period, the hedging performance of asymmetric vech model is the largest. Third, in case of out-of-sample, it is found that BEKK model is best.

Key words: KOSPI 200 futures; hedging effectiveness; vech; CCOR; BEKK

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1. Introduction

Since the KOSPI (Korea Stock Price Index) 200 futures contract was launched on May 3, 1996, it has grown into one of active stock index futures contracts in the world. Many of the participants in KOSPI 200 futures markets aim to reduce or eliminate a particular risk that they face. Since risk is usually measured as the volatility of portfolio returns, the hedgers may be interested in the hedge ratio that minimizes the variance of the returns of a portfolio.

To determine the minimum variance hedge ratio, previous investigations assume that the hedge ratio is constant over time and estimate it using simple ordinary least square (OLS) estimation (see Ederington, 1979) and vector error correction model (VECM) (Ghosh, 1993; Lien and Luo, 1993; Chou, Fan, and Lee, 1996). However, given the time-varying nature of the variance and covariance in many financial markets, the classical assumption of the time-invariant optimal hedge ratio appears inappropriate. A superior performance has been made by adopting an autoregressive conditional heteroskedasticity (ARCH) model (see Cecchetti, Cumby, and Figlewski, 1988), GARCH (generalized ARCH) model (see Baillie and Myers, 1991; Sephton, 1993a; Sephton, 1993b; Brooks, Henry, and Persand, 2002; Poomimars, Cadle, and Theobald, 2003; Wang and Low, 2003; Choudhry, 2004) and SV (stochastic volatility) model (Anderson and Sorensen, 1996; Lien and Wilson, 2001). Except for Brooks et al. (2002), most literatures do not allow for an asymmetric effect across the entire variance-covariance matrix of returns and compare various time-varying models

In this paper, the hedge ratios are estimated by vech model, asymmetric vech model, CCOR (constant correlation) model, asymmetric CCOR model, BEKK model, and asymmetric BEKK model. We examine the difference of hedge effectiveness between symmetric models and asymmetric models using KOSPI 200 futures. Main empirical results show that the conditional variance and covariance varies over time. In the comparison of in-sample, the hedging performance of asymmetric vech model is the largest, indicating that there are big market shocks, for example IMF bailout, for this period. In case of out-of-sample, it is found that BEKK model is best.

The remainder of the paper is organized as follows. Following the introduction, Section 2 describes hedge models. Data and the results of stationarity test are presented in section 3. Section 4 estimates hedge models and analyzes hedging effectiveness. Section 5 concludes the paper.

2. Hedge models

2.1. VECM

There has been some debate in the literature as to whether the two markets must be cointegrated. Ghosh (1993), for example, suggests that market efficiency should imply that cash and futures are cointegrated. We tested the unit root and cointegration of level prices and returns series of KOSPI 200. If these markets are cointegrated, the conditional mean equations of the model employed in this article are a Vector Error Correction Model (VECM), shown as equation (1). In this model, $\varepsilon_t = [\varepsilon_{st}, \varepsilon_{ft}]$ represents the innovation vector from the stock and futures models respectively and $S_{t-1} - \theta F_{t-1}$ represents an error correction term.

$$R_{st} = \beta_{1,0} + \beta_{1,1}(S_{t-1} - \theta F_{t-1}) + \beta_{1,2}R_{st-1} + \beta_{1,3}R_{ft-1} + \varepsilon_{st} \qquad (1)$$

$$R_{ft} = \beta_{2,0} + \beta_{2,1}(S_{t-1} - \theta F_{t-1}) + \beta_{2,2}R_{ft-1} + \beta_{2,3}R_{st-1} + \varepsilon_{ft}$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} | \Phi_{t-1} \sim N(0, H_t) \qquad H_t = \begin{bmatrix} h_{sst} & h_{sft} \\ h_{fst} & h_{fft} \end{bmatrix} ,$$

2.2. vech model

In estimating bivariate vech model, it is required to estimate 21 parameters in the conditional variance-covariance structure, subject to the requirement that H_t be positive-definite. Bollerslev, Engle, and Wooldridge (1988) propose the model restricted the coefficient matrices A and B to be diagonal, where each element of the conditional variance-covariance matrix depends only on its past values and surprises. We use the diagonal vech model (hereafter vech model), presented in equation (2). Equation (3) illustrates asymmetric vech model. In this specification, vech(.) denotes the vector-half operator that stacks the lower triangular elements of an N×N matrix into an [N(N+1)/2]×1 vector.

$$vech(H_t) = C + Avech(\varepsilon_{t-1}\varepsilon'_{t-1}) + Bvech(H_{t-1}) \qquad (2)$$

$$\begin{bmatrix} h_{sst} \\ h_{sft} \\ h_{fft} \end{bmatrix} = \begin{bmatrix} C_{10} \\ C_{20} \\ C_{30} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{st-1} \\ \varepsilon_{st-1}\varepsilon_{ft-1} \\ \varepsilon^2_{ft-1} \end{bmatrix} + \begin{bmatrix} B_{11} & 0 & 0 \\ 0 & B_{22} & 0 \\ 0 & 0 & B_{33} \end{bmatrix} \begin{bmatrix} h_{sst-1} \\ h_{sft-1} \\ h_{fft-1} \end{bmatrix}$$

$$\begin{bmatrix} h_{sst} \\ h_{sft} \\ h_{fft} \end{bmatrix} = \begin{bmatrix} C_{10} \\ C_{20} \\ C_{30} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{st-1} \\ \varepsilon_{st-1}\varepsilon_{ft-1} \\ \varepsilon^2_{ft-1} \end{bmatrix} + \begin{bmatrix} B_{11} & 0 & 0 \\ 0 & B_{22} & 0 \\ 0 & 0 & B_{33} \end{bmatrix} \begin{bmatrix} h_{sst-1} \\ h_{sft-1} \\ h_{fft-1} \end{bmatrix} + \begin{bmatrix} D_{11} & 0 & 0 \\ 0 & D_{22} & 0 \\ 0 & 0 & D_{33} \end{bmatrix} \begin{bmatrix} e^2_{st-1} \\ e_{st-1}e_{ft-1} \\ e^2_{ft-1} \end{bmatrix} \quad (3)$$

$$e_{jt} = \min[\varepsilon_{jt}, 0],\ j = s, f$$

2.3 CCOR model

Bollerslev (1990) shows an invariant measure of the coherence between spot and futures evaluated at time t-1. Of course, in general, this measure of coherence will be time varying as H_t varies over time. However, in some applications the time-varying conditional covariance might be taken as proportional to the square root of the product of the corresponding two conditional variances. Bollerslev (1990) assumes a GARCH(1,1) structure for the conditional variance, but allows for non-zero constant correlation between spot and futures. We use the diagonal CCOR model as equation (4) and the asymmetric CCOR model as equation (5).

$$\begin{bmatrix} h_{sst} \\ h_{fft} \end{bmatrix} = \begin{bmatrix} C_{10} \\ C_{30} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 \\ 0 & A_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{st-1} \\ \varepsilon^2_{ft-1} \end{bmatrix} + \begin{bmatrix} B_{11} & 0 \\ 0 & B_{33} \end{bmatrix} \begin{bmatrix} h_{sst-1} \\ h_{fft-1} \end{bmatrix} \quad (4)$$

$$h_{sft} = \rho\sqrt{h_{sst}h_{fft}}$$

$$\begin{bmatrix} h_{sst} \\ h_{fft} \end{bmatrix} = \begin{bmatrix} C_{10} \\ C_{30} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 \\ 0 & A_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{st-1} \\ \varepsilon^2_{ft-1} \end{bmatrix} + \begin{bmatrix} B_{11} & 0 \\ 0 & B_{33} \end{bmatrix} \begin{bmatrix} h_{sst-1} \\ h_{fft-1} \end{bmatrix} + \begin{bmatrix} D_{11} & 0 \\ 0 & D_{33} \end{bmatrix} \begin{bmatrix} e^2_{st-1} \\ e^2_{ft-1} \end{bmatrix} \quad (5)$$

$$h_{sft} = \rho\sqrt{h_{sst}h_{fft}}$$

$$e_{jt} = \min[\varepsilon_{jt}, 0],\ j = s, f$$

2.4 BEKK model

Engle and Kroner(1995) proposed the Bollerslev, Engle, Kroner, and Kraft(BEKK) parameterization. The BEKK parameterization requires estimation of only 11 parameters in the conditional variance-covariance structure and guarantees H_t to be positive definite. We use the diagonal BEKK model as equation (6) and the asymmetric BEKK model as equation (6).

$$H_t = C'_1 C_1 + A'_1(\varepsilon_{t-1}\varepsilon'_{t-1})A_1 + B'_1 H_{t-1} B_1 \tag{6}$$

$$H_t = \begin{bmatrix} C_{10} & 0 \\ C_{20} & C_{30} \end{bmatrix} \begin{bmatrix} C_{10} & C_{20} \\ 0 & C_{30} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 \\ 0 & A_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{st-1} \\ \varepsilon_{ft-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{st-1} & \varepsilon_{ft-1} \end{bmatrix} \begin{bmatrix} A_{11} & 0 \\ 0 & A_{33} \end{bmatrix}$$
$$+ \begin{bmatrix} B_{11} & 0 \\ 0 & B_{33} \end{bmatrix} \begin{bmatrix} h_{sst-1} & h_{sft-1} \\ h_{fst-1} & h_{fft-1} \end{bmatrix} \begin{bmatrix} B_{11} & 0 \\ 0 & B_{33} \end{bmatrix}$$

$$H_t = \begin{bmatrix} C_{10} & 0 \\ C_{20} & C_{30} \end{bmatrix} \begin{bmatrix} C_{10} & C_{20} \\ 0 & C_{30} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 \\ 0 & A_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{st-1} \\ \varepsilon_{ft-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{st-1} & \varepsilon_{ft-1} \end{bmatrix} \begin{bmatrix} A_{11} & 0 \\ 0 & A_{33} \end{bmatrix} \tag{7}$$
$$+ \begin{bmatrix} B_{11} & 0 \\ 0 & B_{33} \end{bmatrix} \begin{bmatrix} h_{sst-1} & h_{sft-1} \\ h_{fst-1} & h_{fft-1} \end{bmatrix} \begin{bmatrix} B_{11} & 0 \\ 0 & B_{33} \end{bmatrix} + \begin{bmatrix} D_{11} & 0 \\ 0 & D_{33} \end{bmatrix} \begin{bmatrix} e_{st-1} \\ e_{ft-1} \end{bmatrix} \begin{bmatrix} e_{st-1} & e_{ft-1} \end{bmatrix} \begin{bmatrix} D_{11} & 0 \\ 0 & D_{33} \end{bmatrix}$$
$$e_{jt} = \min[\varepsilon_{jt}, 0],\ j = s, f$$

3. Data and stationarity test

3.1. Data description

The data employed in this study comprise 2,503 daily observations on the KOSPI 200 stock index and stock index futures contract spanning the period May 3, 1996 - December 29, 2005. Days corresponding to Korea public holidays are removed from the series to avoid the incorporation of spurious zero returns. To avoid thin trading and expiration effects, the nearest contract is used, rolling over to next nearest contract prior to expiration month of the current contract. These data are collected from Korea Exchange.

Let S_t and F_t represent the logarithms of the stock index and stock index futures prices. The daily return on a spot position held from t-1 to t are calculated R_{st} = $(S_t - S_{t-1})\times 100$. Similarly, the actual return on a futures position is R_{st} = $(F_t - F_{t-1})\times 100$.

Summary statistics for the data are presented in Table 1. Two series show excess kurtosis, implying fatter tails than a normal distribution. This result is backed by the Jarque-Bera statistics. The values of Ljung-Box (hereafter LB) for the return series are significant at the 1% level. The LB (10) for squared return series are highly significant for two markets, suggesting the possibility of the presence of autoregressive conditional heteroskedasticity.

[Insert Table 1]

3.2. Stationarity test

Panel A of Table 2 reports stationarity test results for spot and futures series. ADF (augmented Dickey-Fuller) test and PP (Pillips-Perron) test fail to reject the null hypothesis of the presence of a unit root in both the spot and futures prices, indicating that these series are non-stationary. The hypothesis of the existence of a unit root in the two return series is rejected at the 1% level.

To test for cointegration between spot and futures, Johansen methodology is adopted. The results are reported in Panel B of Table 2. Since 75.441 exceed the 5 percent critical value of the λ_{trace} statistic, it is possible to reject the null hypothesis of no cointegration vectors and accept the alternative of one or more cointegration vectors. Next, we can use he $\lambda_{trace}(1)$ statistic to test the null of $\gamma \leq 1$ against the alternative of two or three cointegrating vectors. Since 8.790 is less than the 5% critical value of 12.25, we can not reject the null hypothesis at this significance level. The value of $\lambda_{\max}$ statistic is such that the null hypothesis of no cointegration ($\gamma = 0$) is soundly rejected and $\gamma = 1$ cannot be rejected. As such, it is evident that there is one cointegrating vector between two series.

[Insert Table 2]

4. The empirical and comparison results

4.1. The estimation of hedge models

Given the evidence of a long-run or cointegrating relationship between S_t and F_t, the conditional mean equations are parameterized as a VECM rather than a VAR to avoid the loss of long-run information. The lag of conditional mean equation decided on 1 using AIC and SBC.

The $\beta_{1,3}$ of all models is significant. The null hypothesis "futures prices do not Granger cause stock prices" is rejected. This suggests that new information tends to be reflected first in futures prices rather than the stock index prices. This results is consistent with the findings of Brooks et. al (2002) and Wang and Low (2003).

The estimated parameters are presented in Table 3. All parameters in variance equations are statistically significant, suggesting that the variances, covariances, and the risk-minimising hedge is indeed changing over time [Wang and Low (2003)]. Significant ARCH process is found in all stock and futures tests. The size of the ARCH parameters (A_{11} and A_{33}) are significant and less than unity. The size and significance of the ARCH parameters indicates volatility clustering in these markets. The covariance parameters (A_{22} and B_{22}) indicate a significant and positive interaction between the two returns. The value of LLR (log likelihood ratio) in the asymmetric vech model is higher than other models. The values of LB (10) for the innovation series and for squared innovation series are not significant at the 5% level, suggesting that hedge models are adequate.

[Insert Table 3]

4.2. In-sample comparisons of hedge ratios and hedging effectiveness

The hedge ratios, computed using the various GARCH models, are reported in panel A of Table 4. All of hedge ratios are less than one, indicating that one to one hedge method is not suitable. Asymmetric BEKK hedge ratio is larger than other hedge ratios.

The panel B of Table 4 reports the resultant portfolio variances and hedging performance using various hedging techniques over in-sample period. To facilitate comparisons, we report the result of naïve hedge($HR_t = 1$) and OLS model. The eight hedging techniques appear to yield lower portfolio variances compared to a naïve hedge. The portfolio variance of asymmetric vech model is smallest. Similarly the hedging performance of asymmetric vech model is larger than other hedging techniques. This implies is that asymmetric vech model shows appropriate hedge ratio and low variance of return because more coefficients than other models are estimated.

When we compare the results between the symmetric and asymmetric models, it is found that the asymmetric models, which allow for an asymmetric response of the conditional variance to positive and negative shocks, show the better performance than symmetric models. The evidence on the asymmetry is consistent with the findings in Brooks et. al (2002).

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[Insert Table 4]

4.3. Out-of-sample comparisons of hedging effectiveness

Table 5 shows the hedging performance using various hedging techniques over out-of-sample period. It appears that variance of return of the BEKK model is smallest and the BEKK model outperforms other model in terms of hedging performance. This is because forecasting power of the BEKK model is superior to that of other models.

The hedging performances of asymmetric hedging techniques are smaller than those of symmetric model for out-of-sample period. However, the difference among hedge models is very small. This is consistent with Choudhry (2004). The reason for these results is that because there are not big market shocks, for example IMF bailout, for out-of-sample (July 1, 2005 - December 29, 2005), KOSPI 200 stock index and futures returns do not have asymmetry. From this point of view, for in-sample, they have asymmetry.

[Insert Table 5]

5. Conclusion

This paper seeks to contribute to current literatures by examining the impact of asymmetries on the hedging of stock index positions and comparing three asymmetric models with three symmetric models. In this study, we examine the hedging effectiveness of stock index futures using the daily data of KOSPI 200 futures in Korea during the period 1996. 5. 3 - 2005. 12. 29. The hedge ratios are estimated by various GARCH models such as vech model, asymmetric vech model, CCOR (constant correlation) model, asymmetric CCOR model, BEKK model, and asymmetric BEKK model and the hedging performances calculated by these models are compared.

Our results indicate that two prices are non-stationary, while two return series are all stationary. From the Johansen method, it is found that there exists cointegration relationship between two prices. We find that asymmetric models, which allow positive and negative price shocks to affect volatility forecasts differently, yield improvements in forecasting in-sample, but not out-of-sample. In the comparison of in-sample, the hedging performance of asymmetric vech model is the largest, indicating that there are big market shocks, for example IMF bailout, for this period. In case of out-of-sample, it is found that BEKK model is best.

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Table 1

Descriptive statistics for spot and futures return series

	Stock	Futures
Mean	0.003	0.003
Variance	0.976	1.229
Skewness	-0.096	-0.020
Kurtosis	2.169	1.750
Jarque-Bera	469.229**	303.208**
LB(10)	38.537**	25.471**
$LB^2(10)$	474.153**	740.404**

LB(n) is the Ljung-Box statistic for up to n lags, distributed as χ^2 with n degrees of freedom.
**, * indicate significance at the 1%, 5% level, respectively.

Table 2
Stationarity test for spot and futures series

Panel A: Unit root test

	ADF	PP
S_t	-0.005 (-2.667)	-0.005 (-2.680)
F_t	-0.006 (-2.746)	-0.006 (-2.849)
R_{st}	-1.058** (-23.776)	-0.914** (-44.523)
R_{ft}	-1.094** (-24.068)	-0.968** (-47.158)

Panel B: Cointegration test

Null Hypothesis	Alternative Hypothesis		1% Critical value	5% Critical value
λ_{trace} test		λ_{trace} value		
$\gamma = 0$	$\gamma > 0$	75.441**	30.45	25.32
$\gamma \leq 1$	$\gamma > 1$	8.790	16.26	12.25
$\lambda_{\max}$ test		$\lambda_{\max}$ value		
$\gamma = 0$	$\gamma = 1$	66.652**	23.65	18.96
$\gamma = 1$	$\gamma = 2$	8.790	16.26	12.25

The t-statistics are reported in parentheses. **, * indicate significance at the 1%, 5% level, respectively. γ is the number of cointegration vector.

Table 3

Maximum Likelihood Estimates for models

Panel A: Estimation results

	VECM	Vech	Asym. vech	CCOR	Asym. CCOR	BEKK	Asym. BEKK
$\beta_{1,0}$	0.266** (0.002)	0.013 (0.018)	-0.011 (0.016)	0.048** (0.016)	0.014 (0.012)	0.003 (0.013)	-0.012 (0.014)
$\beta_{2,0}$	0.319** (0.103)	0.012 (0.020)	-0.010 (0.017)	0.055** (0.016)	0.020 (0.013)	-0.001 (0.014)	-0.010 (0.014)
$\beta_{1,1}$	-0.003** (0.001)	0.012 (0.021)	0.005 (0.015)	0.022 (0.016)	0.019 (0.013)	0.012 (0.016)	0.006 (0.014)
$\beta_{2,1}$	-0.004** (0.001)	0.094** (0.024)	0.084** (0.016)	0.089** (0.019)	0.086** (0.015)	0.096** (0.019)	0.086** (0.017)
$\beta_{1,2}$	-0.523** (0.036)	-0.133* (0.056)	-0.119* (0.057)	-0.091 (0.070)	-0.083 (0.066)	-0.125** (0.047)	-0.106 (0.059)
$\beta_{1,3}$	0.096** (0.031)	0.233** (0.050)	0.213** (0.055)	0.156* (0.064)	0.143* (0.066)	0.236** (0.044)	0.207** (0.055)
$\beta_{2,2}$	0.027 (0.040)	-0.062 (0.055)	-0.081 (0.063)	-0.110 (0.071)	-0.124 (0.074)	-0.064 (0.049)	-0.093 (0.063)
$\beta_{2,3}$	0.505** (0.035)	0.142** (0.060)	0.153** (0.064)	0.135 (0.077)	0.144 (0.075)	0.161** (0.054)	0.176** (0.067)
C_{10}		0.007 (0.004)	0.007** (0.003)	0.006** (0.002)	0.006** (0.002)	0.074** (0.020)	0.089** (0.014)
C_{20}		0.007 (0.004)	0.007** (0.003)			0.071** (0.016)	0.092** (0.014)
C_{30}		0.007 (0.004)	0.008** (0.003)	0.008** (0.002)	0.007** (0.002)	-0.026** (0.005)	-0.018** (0.007)
A_{11}		0.067** (0.006)	0.039** (0.003)	0.086** (0.011)	0.050** (0.004)	0.262** (0.028)	-0.199** (0.027)
A_{22}		0.064** (0.001)	0.040** (0.003)				
A_{33}		0.064** (0.003)	0.040** (0.003)	0.085** (0.011)	0.054** (0.005)	0.254** (0.021)	-0.217** (0.025)
B_{11}		0.929** (0.006)	0.930** (0.008)	0.912** (0.011)	0.915** (0.007)	-0.964** (0.008)	0.963** (0.006)
B_{22}		0.931** (0.006)	0.931** (0.007)				
B_{33}		0.930** (0.008)	0.930** (0.008)	0.912** (0.010)	0.913** (0.008)	-0.966** (0.006)	0.963** (0.005)
D_{11}			0.051** (0.017)		0.066** (0.014)		0.235** (0.034)
D_{22}			0.046** (0.015)				
D_{33}			0.047** (0.016)		0.059** (0.005)		0.191** (0.040)
ρ				0.928** (0.004)	0.929** (0.003)		
LLR		547.988	576.459	345.797	368.379	518.369	550.855

Table 3 (continued)

Panel B: Diagnostic tests

		VECM	Vech	Asym. vech	CCOR	Asym. CCOR	BEKK	Asym. BEKK
R_{st}	LB(10)		6.649 [0.758]	5.793 [0.832]	9.528 [0.483]	9.089 [0.524]	7.105 [0.716]	5.833 [0.830]
	$LB^2(10)$		8.324 [0.597]	8.177 [0.612]	7.677 [0.660]	8.495 [0.581]	8.386 [0.591]	8.266 [0.603]
R_{ft}	LB(10)		8.261 [0.603]	7.652 [0.663]	17.228 [0.069]	16.843 [0.078]	7.940 [0.635]	7.547 [0.673]
	$LB^2(10)$		15.567 [0.113]	14.343 [0.158]	11.730 [0.304]	11.194 [0.343]	16.283 [0.092]	13.854 [0.180]
D.W.		2.288						

LB(n) is the Ljung-Box statistic for up to n lags, distributed as χ^2 with n degrees of freedom. The standard errors are reported in parentheses. The t-statistics are reported in [ ]. **, * indicate significance at the 1%, 5% level, respectively.

Table 4

Hedge ratio and hedging performance (in-sample)

Panel A: Hedge ratio

	VECM	Vech	Asym. vech	CCOR	Asym. CCOR	BEKK	Asym. BEKK
Mean	0.7902	0.8469	0.8445	0.8273	0.8228	0.8467	0.8472
Variance	-	0.0122	0.0124	0.0080	0.0080	0.0129	0.0129

Panel B: Hedging performance

	Volatilities of hedge returns	Hedging performance
naive	0.2372	0.7571
OLS	0.1883	0.8072
VECM	0.1885	0.8070
vech	0.1852	0.8103
Asym. vech	0.1847	0.8110
CCOR	0.1872	0.8084
Asym. CCOR	0.1861	0.8095
BEKK	0.1866	0.8090
Asym. BEKK	0.1862	0.8094

The naïve hedge is $HR_t = 1$.

`Table 5

Hedging performance (out-of-sample)

	Volatilities of hedge returns	Hedging performance
naive	0.0214	0.9122
OLS	0.0179	0.9264
VECM	0.0184	0.9244
vech	0.0163	0.9330
Asym. vech	0.0164	0.9329
CCOR	0.0166	0.9319
Asym. CCOR	0.0169	0.9307
BEKK	0.0162	0.9334
Asym. BEKK	0.0163	0.9333

The naïve hedge is $HR_t = 1$.