ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF, Vol. 7, No. 1, 111–130, 2011

MULTI MEAN GARCH APPROACH TO EVALUATING HEDGING PERFORMANCE IN THE CRUDE PALM OIL FUTURES MARKET

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ABSTRACT

This paper provides evidence of hedging performance in the crude palm oil market using risk minimisation and the investor's utility function measurement. We use the spot and futures crude palm oil daily prices from the period of January 1996 to August 2008. Using a dynamic model, we estimate three different mean specifications that involve the intercept, Vector Autoregressive (VAR) and Vector Error Correction Model (VECM) within the Baba, Engle, Kraft and Kroner (BEKK) model. The risk minimisation results exhibit that the Intercept-BEKK and VAR-BEKK models tend to give the most variance reduction within the in-sample and out-sample analysis, respectively. However, Intercept-BEKK remains to outcast the other models in giving the most utility function. The empirical evidence shows that different mean specifications will generate varying hedging performance results, especially in relation to the risk minimisation result. However, the difference in the performance among the tested models is small, especially within the investor's utility function measurement. Since a more sophisticated model does not warrant better hedging performance results, we suggest that a parsimony model may be appropriate when improvising the hedging performance.

Keywords: Hedging performance, hedging ratio, BEKK model, minimum variance, mean variance

INTRODUCTION

The hedging ratio is an important parameter that influences the estimation of hedging portfolio returns, variances and, finally, the hedging strategy performance. The debate on whether a constant hedging ratio or non-constant hedging ratio gives the highest hedging effectiveness result has run for many years. Most empirical evidence infers that a non-constant hedging ratio gives higher risk reduction than a constant ratio. In addition, when a non-constant ratio is considered, the exclusion of the long run effect (Error Correction Model) in this dynamic modelling process tends to generate a downward bias hedging ratio (Lien, 2004). Because the hedging ratio estimation is affected, we believe that the mean specification in the dynamic modelling process plays a vital role in measuring the hedging performances in any futures market.

This study contributes to the existing empirical evidence in a number of ways. First, most of the literature highlights various variance specifications in GARCH modelling, and determines which model performs better in hedging ratio estimation and hedging performance. Less attention is given to investigating whether different mean specification models could also have a nontrivial effect on the hedging performance measurement result. To address this issue, this research attempts to investigate the effect of three different mean specifications comprising the intercept, Vector Autoregressive (VAR henceforth) and Vector Error Correction Model (VECM henceforth) applied in the modified Baba, Engle, Kraft and Kroner (1990) Model (BEKK model henceforth) on hedging effectiveness in the crude palm oil futures market. Second, attention is also given to studying the hedging effectiveness in both the risk minimisation and investor's utility function frameworks concurrently. Hence, in this study, the hedging performance will be examined based on the variance reduction comparison and utility investor maximisation function within the BEKK framework. Finally, the study extends the existing line of research on the emerging commodity futures market. These countries rely more on agricultural-based export income than on industrial-based income. In addition, the instability of commodity prices may affect the emerging countries' overall economic performance. For example, Eichengreen (2002) infers that any uncertain fluctuation in commodity prices will translate into higher inflation volatility in these emerging countries more rapidly than in the advanced countries. As such, the analysis of hedging performances in these emerging countries is more crucial than in the developed market, as the agricultural industry has a direct impact on the countries' economic performance.

The remainder of this paper is structured as follows. First, we discuss the evidence of hedging performance measurement investigation by precedent researchers. The next section explains the dynamic model and the two hedging performance techniques adopted in the study. Then, we describe the data used for this research, and the empirical results that are generated from the tested models. This section is followed by the hedging performance results through variance comparison and utility maximisation for each of the tested models. The last section concludes the paper.

LITERATURE REVIEW

Theoretically, hedging in the futures market will downsize the price risk (volatility) to which traders are exposed. The effectiveness of the hedging strategy (hedging performance) is measured by computing the risk reduction being achieved by the hedging portfolio compared to the unhedged portfolio (which refers to the minimum variance framework). An impressive literature has focused on hedging performance within the risk minimisation context (Ederington, 1979). However, some believe that true hedging performance should be measured by considering both the risk and the return aspects. These risk and return aspects work within the investor's utility maximisation framework or the Markowitz mean variance framework (see Kroner & Sultan, 1993; Gagnon & Lypny, 1995; Gagnon, Lypny, & McCurdy, 1998; Yang & Allen, 2004). The mean-variance framework plays a vital role in making sense of financial theories, especially the portfolio theory. Together, the hedging and portfolio theories will establish the hedging performance measurement framework. Working (1953) emphasises that hedgers not only aim to reduce risk but also consider the profit maximisation goal because market participants do not constantly engage in hedging.

In hedging performance measurements, researchers estimate the second moments of both spot and futures returns, then derive the optimal futures contract implemented for each spot contract (or hedging ratio). The hedging ratio has a direct impact on estimating the hedging portfolio returns, variances and, finally, the strategy performance. Conventionally, the hedging performance can be measured by computing the minimum variance hedging ratio.[1] This ratio is also known as the myopic hedging ratio. Ederington (1979) used this classical methodology (OLS) to estimate the hedging ratio in the Government National Mortgage Association. This method does not consider the surrounding information that may influence the changes of hedging decision and turns the hedging decision to be time varying. However, the myopic hedging ratio estimation is proven to give a bias hedging ratio, which will lead to an inaccurate percentage of risk minimisation (Ederington & Salas, 2008).

In addition, overwhelming evidence highlights that heteroscedasticity and serial correlation issues exist in most financial data. These issues mean that the conventional estimation is less appropriate because OLS assumes variance and covariance of spot and assumes that futures tend to be monotonic in fashion, although the ARCH framework shades the light to overcome these issues. Over time, more empirical evidence reveals that the time factor present in most spot and futures returns could affect the hedging decision. The hedging performance measurement can be achieved using the univariate ARCH and GARCH framework. Cecchetti, Cumby and Figlewski (1988) were among the pioneers to investigate the hedging performance in Treasury bonds and the T-bond market within the univariate ARCH family framework.

Engle (1982) and Bollerslev (1986) developed a more general model (GARCH), which is an extension of the ARCH model where the model considers the dynamic conditional second moments. The GARCH framework further acknowledges the time factor in estimating the second moment's return and allows the capture of its own long run shocks. In addition, the model is a flexible model that can accommodate a fat-tailed distribution in most spot and futures prices. Many researchers have used the GARCH framework to model the higher moments in variety commodity markets (Baillie & Myers, 1991; Fackler, 1992; Bera, Gracia, & Roh, 1997; Foster & Whitemen, 2002, and in developed financial markets (Bollerslev, 1987; Baillie & Bollerslev, 1989; Kroner & Sultan, 1993; Wilkinson, Rose, & Young, 1999; Mili & Abid, 2004; Yang & Allen, 2004; Floros & Vougas, 2004) but only Ford, Pok and Poshakwale (2005) studied the developing market *inter alia*.

Until now, a variety of advanced GARCH models have been introduced to improvise the second moment estimation process. In hedging performance measurement, the estimation process is closely related to model the behaviour of the return in both spot and futures markets. In addition, previous researchers preferred to adopt the general BEKK model in their hedging performance studies. Additionally, the model is found to be more flexible and it can be tailored according to the researcher's requirement. Moschini and Myers (2002) and Ford, Pok and Poshakwale (2005) demonstrated the flexibility of the BEKK model by imposing a restriction to test the equality of constant or non-constant hedging ratio hypotheses. They infer the superiority of a non-constant hedging ratio over a constant one. Additionally, the model also allows for testing of the asymmetric effect on hedging performance results (see Brooks, Hendry, & Persand, 2002; Malo & Kanto, 2005; Switzer & El-Khoury, 2006). However, the evidence supports that the asymmetric BEKK model promised a better risk reduction result the improvement is relatively smaller than the symmetric BEKK model. Using the BEKK model, Lee and Yoder (2007) introduced the regime shift effect within the hedging performance results in the Corn and Nickel market. They found that the regime switching BEKK model is marginally superior in reducing the hedged portfolio than the general BEKK model. Based on precedent studies, we can conclude that there is no conclusive answer to which model generates the best hedging performance results. However, the one obvious finding is that the dynamic hedging ratio succeeds in almost all hedging performance investigations in the various markets tested, as compared to the myopic hedging ratio.

In multivariate GARCH models, the framework offers flexibility of specifications in modelling the conditional variance specifications and provides ample alternatives in modelling the mean conditional return. This framework provides different mean models, including both the simple constant and an error correction model. Baillie and Myers (1991), Gagnon and Lypny (1995), and Ford, Pok and Poshakwale (2005) documented the mean specification via the constant or intercept model in their hedging effectiveness studies. However, Lien, Tse and Tsui (2002), and Floros and Vougas (2004) considered VAR specification, which focused on short-run behaviour in spot and futures prices or return. Nevertheless, empirical evidence highlights the existence of a long-run relationship between spot and futures returns, and many documented this long-run effect in their mean specification (Kroner & Sultan, 1993; Lien & Tse, 1999; Wilkinson, Rose, & Young, 1999; Moschini & Myers, 2002; Lien, 2004; Mili & Abid, 2004; Yang & Allen, 2004; Floros & Vougas, 2004) *inter alia*. Additionally, Lien (2004) specifies that the non-inclusion of the long-run effect in the mean return specification tends to generate a lower hedging ratio. A similar result was reported in the estimation of the Australian stock index futures hedging ratio (Yang & Allen, 2004). In contrast to the evidence portrayed above, Wilkinson, Rose and Young (1999) and Floros and Vougas (2004) found that the ECM model tends to give a lower hedging ratio than the conventional models. Overall, the evidence reveals that the different restrictions imposed in the mean conditional model could affect the hedging ratio estimation results. Hence, we posit that the selection of restrictions implemented in modelling the conditional spot and futures mean returns could likely affect the hedging performance results.

METHODOLOGY

In this study, the daily settlement prices are transformed into a natural log return, which is computed as follows:

$$\text{Return} = 100 \times [\ln(P_{t+1} / P_t)] \tag{1}$$

where P_{t+1} is settlement price of crude palm oil spot (CPO henceforth) or crude palm oil futures (FCPO henceforth) for period $t + 1$ and P_t is settlement price of CPO or FCPO for period t. Next, using these returns we adopt three mean specifications, namely, intercept, VAR and the VECM model, within the BEKK framework in estimating the conditional mean and variance-covariance matrices for both series. Finally, using the estimated conditional mean, variance and covariance, we further proceed to measure the hedging performances using risk minimisation and the investor's utility function. We forecast the hedging performance within the in-sample[2] and out-sample[3] analysis for the 1, 5, 10, 15 and 20 days forecasted period ahead.

Econometric Specification

Many researchers have used the BEKK model to measure hedging performances in many developed futures markets. However, in this study we estimate three different mean conditional specifications that encompass the BEKK-GARCH model. First, we consider a simple intercept mean modelling that was adopted by Baillie and Myers (1991), Tong (1996), Ford, Pok and Poshakwale (2005), Switzer and El-Khoury (2006) and Lee and Yoder (2007). The intercept model is defined as follows:

$$r_{st} = \alpha_s + \varepsilon_{st}\,;\ \varepsilon_{st}\left|\Omega_{t-1}\right. \sim N(0,H_t) \tag{2}$$

$$r_{ft} = \alpha_f + \varepsilon_{ft}\,;\varepsilon_{ft}\left|\Omega_{t-1}\right. \sim N(0,H_t) \tag{3}$$

where r_{st} and r_{ft} represent the return for spot and futures, Ω_{t-1} defines the past information at period $t-1$, α represents the constant and ε is the residual series. Second, for vector autoregressive, we model the conditional return considering both series returns lagged term. The model is able to recognise the short-term association between spot and futures returns. The model is specified as follows:

$$r_{st} = \alpha_s + \sum_{i=1}^{k}\alpha_{s1} r_{s,t-i} + \sum_{i=1}^{k}\alpha_{f1} r_{f,t-i} + \varepsilon_{st} \tag{4}$$

$$r_{ft} = \alpha_f + \sum_{i=1}^{k}\alpha_{f2} r_{f,t-i} + \sum_{i=1}^{k}\alpha_{s2} r_{s,t-i} + \varepsilon_{ft} \tag{5}$$

where α_s and α_f denote the constant term, α_{s1} , α_{f1}, α_{s2} and α_{f2} are parameters and ε_{st} and ε_{ft} residuals are independently, identically distributed random vectors.

However, in the third model we include a long-term relationship in estimating the conditional mean. When both series are integrated at 1, or are stationary at the first difference, there is a tendency of both series to be cointegrated in the long run. We employed the Johansen co-integration test to identify the existence of the long-run relationship between series. The long-run equilibrium between spot and futures returns can be tested by including the error term in the VAR model (VECM). The VECM is expressed as follows:

$$r_{st} = \alpha_s + \sum_{i=1}^{k} \alpha_{s1} r_{s,t-i} + \sum_{i=1}^{k} \alpha_{f1} r_{f,t-i} + e_s Z_{t-1} + \varepsilon_{st} \tag{6}$$

$$r_{ft} = \alpha_f + \sum_{i=1}^{k} \alpha_{f2} r_{f,t-i} + \sum_{i=1}^{k} \alpha_{s2} r_{s,t-i} + e_f Z_{t-1} + \varepsilon_{ft} \tag{7}$$

where α_s and α_f are the constant terms for spot and futures returns, and α_{s1}, α_{f1}, α_{s2}, α_{f2}, e_s and e_f are parameters. Meanwhile, ε_{st} and ε_{ft} are residual series and Z_{t-1} ($r_{s,t-1} - \beta_s - \theta r_{f,t-1}$) denotes the error correction term that measures the deviation from its long-term equilibrium. Yang and Allen (2004), and Floros and Vougas (2004) documented the VAR and VECM model in estimating the constant hedging ratio. In contrast, this study uses these two models for the conditional mean return specification and to estimate the dynamic hedging ratio.

The hedging performance estimation process depends on modelling the characteristic of return in both spot and futures markets. As such, many researchers prefer to use the BEKK model to estimate the conditional variance and covariance matrices for both spot and futures series. Moreover, the model, developed by Baba, Engle, Kraft and Kroner (1990), captures the behaviour of the conditional variance and covariance and maintains the positive definiteness of the estimated parameters. Additionally, Moschini and Myers (2002), and Ford, Pok and Poshakwale (2005) suggest that the BEKK model is a flexible model that can be tailored according to the researcher's requirement. The BEKK model offers flexibility, while at the same time retaining the positive definiteness in parameters generated from the model, this study used this model in estimating both CPO and FCPO variance-covariance matrices. For the purpose of this research, we adopted the modified BEKK model that was introduced by Engle and Kroner in 1995. A general modified BEKK model is encompassed within a basic GARCH (1, 1) model, and the model defines the H_t as follows:

$$H_t = C^{*\prime} C^* + \sum_{k=1}^{K} A_k^{*\prime} \varepsilon_{t-1} \varepsilon_{t-1}^{\prime} A_k^* + \sum_{k=1}^{K} G_k^{*\prime} H_{t-1} G_k^* \tag{8}$$

where $C^* = \begin{bmatrix} C_{ss} & C_{sf} \\ 0 & C_{ff} \end{bmatrix}$, $A_k^* = \begin{bmatrix} A_{ss} & A_{sf} \\ A_{fs} & A_{ff} \end{bmatrix}$ and $G_k^* = \begin{bmatrix} G_{ss} & G_{sf} \\ G_{fs} & G_{ff} \end{bmatrix}$. While, $\varepsilon_t = \begin{bmatrix} \varepsilon_{ss} \\ \varepsilon_{ff} \end{bmatrix}$ and $H_t = \begin{bmatrix} H_{ss} & H_{sf} \\ H_{fs} & H_{ff} \end{bmatrix}$. C_{ss} , A_{ss} and G_{ss} represent the constant, squared residual and volatility lagged coefficient parameters for CPO, while C_{ff},

A_{ff} and G_{ff} represent the similar coefficient parameters for FCPO. C_{sf}, A_{sf}, A_{fs}, G_{sf} and G_{fs} denote the covariance coefficient parameters. ε_{ss} and ε_{ff} are the CPO and FCPO residual parameters, respectively. K is the summation limit, which determines the model generality, and is assumed to be 1. According to Engle and Kroner (1995), when $K > 1$ and there is no restriction imposed in A_k^* matrices, some of A_k^* will produce a similar matrix structure. Consequently, an identification problem will occur. To overcome this identification issue (when $K > 1$), we need to include some restriction on A_k^* matrices. To retain the parsimony principle in the GARCH modelling process, a more general BEKK model with $K = 1$ will be applied in this study because of the high insurability of the positive definiteness without any additional limitation imposed on A_k^* and G_k^*.

Hedging Performance Measurement

The previous section explained the techniques used to estimate the conditional mean (refer to equations 2 through 7) and the variance and covariance matrices (refer to equation 8) for both CPO and FCPO series. We next proceed to examine the hedging performance in the CPO market encompassing the mean variance and minimum variance framework.[4] The minimum variance framework or risk minimisation was developed by Ederington in 1979. His definition of hedging effectiveness is derived from measuring the risk reduction attained by hedgers as compared to non-hedgers. The variance in both spot and futures markets as a proxy for both unhedged and hedged portfolios. The hedging effectiveness can be computed as follows:

$$HE = \left(1 - \frac{Var(HE)}{Var(UnHE)}\right) = \rho^2 \tag{9}$$

where the hedging effectiveness is equal to the squared correlation between the spot and futures returns. *Var(UnHE)* represents the unhedged portfolio, where $VAR(UNHE) = X_s^{\ 2}\sigma_s^{\ 2}$ (σ_s^2 denotes the variance for CPO return, and X_s^2 is assumed to be equal to one, so the variance of the unhedged portfolio will be equal to the variance for spot return), and *Var(HE)* refers to the variance of the hedging position where $VAR(HE) = \sigma_s^{\ 2} + h^2\sigma_f^{\ 2} - 2h\sigma_{sf}$ and h represents the optimal futures contracts held against the spot contracts or hedging ratio. The hedging ratio is assumed to be time varying and the ratio can be estimated using

$h_t|\Omega_{t-1} = \frac{\text{cov}_{sf}}{\sigma_f^2}|\Omega_{t-1}$ where cov_{sf} denotes the covariance between the CPO and FCPO.

Alternatively, hedging performance can also be measured through the mean-variance framework or the investor's utility maximisation function comparison. The investor's utility maximisation function is calculated by comparing the hedging portfolio mean return with the variance attained for each investment strategy, taking into consideration the level of risk aversion of the investors. It is worth noting here that the research is not focused on estimating the best utility maximisation that could be attained by hedgers. Instead, the study is focused on identifying the significant changes in investor's utility maximisation when different mean and variance specifications are adopted (at a given range of level risk aversion). Gagnon, Lypny and McCurdy (1998) lay out the utility maximisation of each investor as follows:

$$\underset{h}{MAX} = \left\{E(RH_t|\Omega_{t-1}) - 1/2\phi VAR(RH_t|\Omega_{t-1})\right\} \tag{10}$$

where RH_t is equal to the return of the hedging portfolio ($RH_t = r_s - hr_f$ where r_s and r_f denote CPO and FCPO return, while h is the hedging ratio); Ω_{t-1} defines the surrounding information at period $t - 1$; Φ is the risk tolerance considered by investors; and $VAR(RH_t)$ represents the variance of hedging portfolio. A similar measurement was reported by Yang and Allen (2004) for the Australian stock index futures hedging performance.

DATA

In this study, the daily settlement prices for CPO, which represent the CPO spot commodity market, are collected from the Malaysian Palm Oil Board (MPOB). Meanwhile, the daily settlement CPO futures (FCPO henceforth) prices are collected from the Bursa Malaysia Derivative Berhad and Bloomberg databases. The CPO and FCPO daily settlement prices are used over the period of 2 January 1996 to 15 August 2008.[5] FCPO is a Ringgit Malaysia denominated Crude Palm Oil futures contract, which trades in Bursa Malaysia Derivative Berhad. FCPO is introduced to strengthen the CPO prices and further facilitate market participants (direct producers and buyers) in managing their price risk effectively within the local context without engaging beyond the international futures market. The promising growth and prospects of the crude palm oil industry encouraged Bursa Malaysia to introduce FUPA, a US Dollar denominated palm oil futures contract, in September 2008. However, the study will only use FCPO to represent the CPO futures market.

EMPIRICAL EVIDENCE

Based on the diagnostic test results[6], we conclude that both series have fat-tail and non-normality distribution features. In addition, the tested series are only stationary at its first difference. The preliminary evidence supports that CPO and FCPO tend to have a serial correlation and ARCH effect problem.[7] As such, the GARCH framework is able to overcome these issues and provide a better technique for capturing more precise variance, based on behaviour in both series. In Table 1, we can see that the CPO and FCPO variances are more highly influenced by their own volatility shocks (refer to total G_{ss} and G_{ff}) than by their own squared residuals (refer to total A_{ss} and A_{ff}), especially in the Intercept and VECM BEKK models. The residual and squared residual diagnostic results indicate that both the VAR-BEKK and VECM-BEKK models are able to solve the serial correlation and ARCH issues in both residual series. However, the Intercept model appears to provide the least efficiency in addressing both serial correlation and ARCH issues compared to the other models.

Table 1
Maximum likelihood estimation for BEKK model
This table reports joint maximum likelihood estimates of the conditional means and the covariance matrix of the returns of CPO and FCPO for the following BEKK specification:

	BEKK				BEKK		
	Intercept	**VAR**	**VECM**		**Intercept**	**VAR**	**VECM**
	Mean Specification				**Variance-Covariance Specification**		
α_s	–0.0137	0.0111	0.0024	C_{ss}	0.2293***	0.1943***	–0.2512***
α_f	–0.0195	0.0156	–0.0258	C_{sf}	–0.1461***	0.1392***	0.3664***
α_{1st-1}		–0.2028***	–0.1386***	C_{ff}	–0.601-E6	0.87-E6	–0.1873-E5
α_{1st-2}		–0.1342***	–0.1281***	A_{ss}	–0.3111***	–0.2568**	–0.5893***
α_{1st-3}		–0.0905***	–0.0404*	A_{sf}	–0.0633	0.04931	–0.0191
α_{1st-4}		–0.0342	0.00436	A_{fs}	–0.1769***	–0.1017	0.2807**
α_{1st-5}		–0.0092	0.0419**	A_{ff}	–0.0273	–0.2604***	–0.2554*
α_{1st-6}		–0.0108		G_{ss}	–0.5669***	–0.1319***	–0.2492
α_{1ft-1}		0.3945***	0.3208***	G_{sf}	0.4643***	–0.4375***	0.0535**
α_{1ft-2}		0.191***	0.1592***	G_{fs}	–0.3850***	0.3253***	0.8648***
α_{1ft-3}		0.1024***	0.0807***	G_{ff}	–1.1543***	–0.6701***	0.5346**
α_{1ft-4}		0.0528*	0.022				
α_{1ft-5}		0.03779*	–0.0291				
α_{1ft-6}		0.0424*					
e_s			–9.8826***				
α_{2ft-1}		–0.1205***	–0.0744**				
α_{2ft-2}		–0.1081***	–0.0329				
α_{2ft-3}		–0.1393***	–0.031				
α_{2ft-4}		–0.1237***	–0.0235				
α_{2ft-5}		–0.1092***	–0.0179				
α_{2ft-6}		–0.0876***					

(*continued*)

Table 1 (*continued*)

	BEKK			BEKK		
	Intercept	**VAR**	**VECM**	**Intercept**	**VAR**	**VECM**
	Mean Specification			**Variance-Covariance Specification**		
α_{2st-1}		0.2162***	0.1385***			
α_{2st-2}		0.1762***	0.0747**			
α_{2st-3}		0.1444*	0.0671**			
α_{2st-4}		0.1475***	0.0541**			
α_{2st-5}		0.1057***	0.0137			
α_{2st-6}		0.0879***				
e_f			7.254***			

Note: *** represents a significance level of 1%, ** represents a significance level of 5% and * represents a significance level of 10%. The Intercept-BEKK is estimated using equations 2 and 3, and VAR-BEKK is estimated using equations 4 and 5. The VECM-BEKK model is generated from equations 6 and 7. The number of lags in the VAR model is based on the lag length criteria test results. The total G_{ss} for the Intercept, VAR and VECM models is 0.906, 0.037 and 0.379. The total A_{ss} for the Intercept, VAR and VECM models is 0.238, 0.128 and 0.095, respectively. In addition, the total G_{ff} for the Intercept, VAR and VECM models is 0.476, 1.23 and 0.346, respectively. However, the total A_{ff} for the same three models is 0.008, 0.044 and 0.075, respectively.

Minimum Variance (Risk Reduction)

Table 2
Hedging performance results within minimum variance framework

BEKK Model									
	Hedging Ratio Estimation[a]	Variance (UHP)[b]	Variance (HP)[c]	Percentage Risk Minimisation (%)[d]		Hedging Ratio Estimation[a]	Variance (UHP)[b]	Variance (HP)[c]	Percentage Risk Minimisation (%)[d]
Out-sample Forecasting					**In-sample Forecasting**				
Mean Specification : Intercept									
No. of days forecast					No. of days forecast				
1 day	0.38	0.76	0.55	27.30%	1 day	0.21	0.78	0.73	6.81%
5 days	0.48	1.77	1.19	32.88%	5 days	0.76	1.53	0.85	44.36%
10 days	0.48	1.98	1.38	30.46%	10 days	0.32	1.05	0.86	18.06%
15 days	0.5	1.81	1.18	34.65%	15 days	0.74	2.07	0.71	65.84%
20 days	0.61	1.25	0.39	68.68%	20 days	1.43	5.42	1.64	69.81%
Mean Specification : VAR									
No. of days forecast					No. of days forecast				
1 day	0.61	1.32	0.79	40.21%	1 day	0.17	0.86	0.82	4.70%
5 days	0.53	1.93	1.24	35.94%	5 days	0.24	1.84	1.7	7.45%
10 days	0.53	1.84	1.13	38.93%	10 days	0.4	1.25	0.92	26.35%
15 days	0.48	1.87	1.23	34.19%	15 days	0.42	1.6	1.09	31.80%
20 days	0.49	1.93	1.3	32.77%	20 days	0.64	3.51	1.99	43.24%
Mean Specification : VECM									
No. of days forecast					No. of days forecast				
1 day	0.47	1.65	1.34	18.81%	1 day	0.17	0.97	0.93	4.31%
5 days	0.53	1.81	1.07	40.57%	5 days	0.29	1.75	1.58	9.80%
10 days	0.54	2.07	1.33	35.81%	10 days	0.38	1.17	0.9	22.92%
15 days	0.49	1.44	0.78	45.94%	15 days	0.42	1.56	1.07	30.95%
20 days	0.49	1.44	0.79	45.36%	20 days	0.65	3.49	1.88	46.08%

Note: a – The hedging ratio is calculated based on $h_t|\Omega_{t-1} = cov_{sf}|\Omega_{t-1}/\sigma_f^2|\Omega_{t-1}$.
b – The variance of unhedged portfolio is generated from the variance of CPO (Var (UnHE) = σ_s^2).
c – The variance of hedged portfolio is computed based on Var (HE) = $\sigma_s^2 + h^2\sigma_f^2 - 2h\sigma_{sf}$.
d – The hedging effectiveness or risk reduction is calculated based on $HE = [1 - Var(HE)*/Var(UnHE)] = \rho^2$.

Using the conditional mean, variance and covariance generated from the three models, we extend our analysis on hedging performance measurement. Table 2 reports the hedging performances through the percentage of risk reduction achieved by all three mean models for the BEKK model. The table is segregated according to the out-sample and in-sample data for each model. The results include each of the 1, 5, 10, 15 and 20 day forecasted periods, which are categorised according to the hedging ratio, mean of the hedging portfolio, variance in unhedged portfolio, and the percentage of risk minimisation. The Intercept model predicts a wider range of hedging ratio within 0.21 to 1.43 compared to the out-sample ratio, which is from 0.38 to 0.61. However, a stable estimation was postured by both the VECM-BEKK and VAR-BEKK model within the out-sample data of between 0.48 and 0.61. These ranges of hedging ratio estimation results convey a time varying or non-monotonic characteristic of hedgers' hedging decisions. This evidence indicates that hedgers tend to revise their hedging decisions upon consideration of the surrounding information available in the market.

Interestingly, the Intercept-BEKK model demonstrates a higher time horizon, which leads to a higher hedging ratio estimation. Subsequently, a contrasting finding is reported for the VAR-BEKK model, which predicts an inverse relationship between the hedging ratio and the forecasting period ahead. Within the in-sample period, the VAR and VECM-BEKK exhibit a similar finding to that generated in the Intercept-BEKK model. The evidence supports a positive relationship between the hedging ratio and the percentage of risk reduction, where the lower the ratio is, the lower risk reduction will be achieved by hedgers and vice versa.

The hedging performance results show that the Intercept-BEKK model is likely to give the highest variance reduction, 60% for in-sample data (15-and 20-day forecasting period) and out-sample data (20-day forecasting period). However, the Intercept-BEKK model appears to generate the worst performance for the 1-day forecasted period. During that day, the hedgers are only able to minimise 4% from their total price risk exposure (within the in-sample period).

In conclusion, there is no definite answer as to which model should be accepted as the best model in achieving the greatest risk reduction via hedging portfolio, as compared to the non-hedging position. Although the evidence is mixed, we can conclude that the Intercept-BEKK tends to outcast the other model for the 5, 15 and 20-day periods for in-sample and the 20-day forecasting period for out-sample estimation. These results do not fully support that the VECM model is superior in terms of variance, in comparison to other dynamic models, which is similar to the findings reported by Kroner and Sultan (1993), Yang and Allen (2004) and Ford, Pok and Poshakwale (2005).[8]

Mean Variance Framework Results

Table 3
Hedging performance in the utility maximisation function for the BEKK model

Φ	Intercept-BEKK	VAR-BEKK	VECM-BEKK	Φ	Intercept-BEKK	VAR-BEKK	VECM-BEKK
In-sample Comparison				Out-sample Comparison			
0.5	–0.4264343	–0.9590828	–1.1011248	0.5	–0.1000179	–0.747267	–0.7490781
1	–0.6764343	–1.2090828	–1.3511248	1	–0.3500179	–0.997267	–0.9990781
1.5	–1.4264343	–1.9590828	–2.1011248	1.5	–1.1000179	–1.747267	–1.7490781
2	–2.9264343	–3.4590828	–3.6011248	2	–2.6000179	–3.247267	–3.2490781
2.5	–5.4264343	–5.9590828	–6.1011248	2.5	–5.1000179	–5.747267	–5.7490781
3	–9.1764343	–9.7090828	–9.8511248	3	–8.8500179	–9.497267	–9.4990781

Note: Utility maximisation function for hedging portfolio and unhedged portfolio are computed based on 20-days forecasting period ahead. The utility quadratic function is generated from equation 10 and the Φ denotes the degree of risk aversion for investors ranging from 0.5 to 3.0.

Whereas the previous section discussed the performance of hedging strategies using the minimum variance framework, this section describes the hedging performance within the utility maximisation framework. The hedger's utility results for all estimation models are presented in Table 3. The framework measures the performance of such a strategy, considering the mean return, risk aversion and variance attained in the hedging strategy. Previous researchers have compared the static and the non-static model and have found that the largest utility maximisation was achieved by the non-static model (Kroner & Sultan, 1993; Gagnon & Lypny, 1995; Yang & Allen, 2004). In this study, we do not include the transaction cost but intend to compare the utility maximisation within the BEKK model.

The utility maximisation function analysis is considered using a 0.5 to 3.0[9] risk aversion level within the 20 days of forecasting ahead (in-sample and out-sample). The results support that the Intercept model outperforms in both in-sample and out-sample data within the three GARCH models. However, overall, the Intercept–BEKK model gives the largest utility maximisation within the in-sample and out-sample period. In contrast, the VECM model tends to perform the worst. The results further support that the higher the level of a hedger's aversion, the less the utility maximisation function is achieved. In addition, empirical evidence supports a lower mean return posture in the dynamic models as compared to the static models (Yang & Allen, 2004). Intuitively, when investors have a higher risk aversion it conveys a lower tolerance towards the additional risk exposed by them. Furthermore, a higher level of risk aversion (Φ) will lead to a larger variance $\{ \left| 1/2\varphi VAR(RH_t \middle| \Omega_{t-1}) \right\}$. The imbalance between the mean return and the variance will ultimately result in a larger negative utility maximisation achieved by the hedgers, especially when the return portion $\left\{ E(RH_t | \Omega_{t-1}) \right\}$ is small. It is possible to have negative utility maximisation function results based on similar negative results reported by Yang (2001), Kroner and Sultan (1993) and Yang and Allen (2004).

CONCLUDING REMARKS

Initially, the research investigates whether various mean specifications have a significant effect on the hedging effectiveness in the CPO markets. The study focuses on the Intercept, VAR and VECM mean modelling for the BEKK model. The study attempts to prove evidence for the importance of various mean specifications that may give different hedging performance results. As the findings are focused on hedging performance measurement, the empirical evidence only provides an important implications for academics rather than for policymakers or practitioners. Referring to the diagnostic tests, we find the existence of non-normality features in both the CPO and FCPO series. Both serial correlation and autoregressive and heteroscedasticity problems were established in both residuals and squared residuals, respectively. Consequently, dynamic models are more appropriate for modeling the time varying second moment of the CPO spot and futures returns. The VAR-BEKK is found to fit with the CPO and FCPO. The model is able to solve both the serial correlation and ARCH effect present in both residual and squared residual series; however, the VECM model is likely to partly overcome the issues. It is not surprising that the intercept model is acknowledged to be less satisfactory among all the models in overcoming the serial correlation and ARCH issues, because the means are run only against its intercept. Therefore, it is a foreseen result that the intercept model is less satisfactory than the other models.

The hedging ratio estimation results are proven to be in a non-monotonic process that is consistent with prior empirical evidence. Referring to the variance reduction, the results are mixed and the Intercept-BEKK model appears to be the best within the in-sample forecasted periods (20 days). In addition, when the utility investor's maximisation function is considered, the Intercept–BEKK model tends to be superior for both in-sample and out-sample analysis. It is also revealed that when hedgers are willing to tolerate the risky position, it elevates the hedger's utility level. Overall, the findings acknowledge that the error term mean specification could influence the degree of risk minimisation; however, the magnitude is low. Nevertheless, interestingly, the intercept model appears to be superior when it is judged against the investor's utility maximisation function. In conclusion, the evidence supports that different specifications in conditional mean models tend to affect both the degree of risk minimisation and the hedger's utility maximisation. It is interesting to note that researchers need to maintain a less complex concept in modelling the hedging performance measurement because a complicated model may not give the best hedging performance result.

NOTES

1. Refers to the slope of changes in futures prices with regards to changes in spot prices.
2. The in-sampling data period is analysed between January 1996 and December 2007.
3. The out-sampling period is analysed between January 2008 and August 2008.
4. Using the generated conditional variance-covariance, we continue to compute the hedging performance within the risk reduction or minimum variance framework. Furthermore, we use the generated conditional mean and variance-covariance to evaluate the hedger's risk and return trade off or mean variance framework.
5. This study is a part of the author's PhD thesis that catered for the events from Asian Financial crisis to current global recession periods. In addition, we accessed the related databases on 16 August 2008; hence the sampling data were collected prior to the Asian Financial Crisis up to 15 August 2008.
6. The study adopted three types of unit root tests including the Augmented Dickey Filler (ADF henceforth) test, Phillip-Perron (PP henceforth) test and Kwiatkowski, Philips, Schmidt, and Shin (KPSS henceforth) test. Subsequently, the cointegration relationship between the series was detected by the Johansen Cointegration test. Then the Ljung-Box test and correlograms of squared residuals were done to infer the existence of serial correlation and ARCH effect in the tested series.
7. Due to space constraints, we are not able to include the details of the diagnostic test results.
8. Static better than VECM model.
9. The 0.5 aversion level simply means that the market participant is a risk taker or risk seeker, and this group of investors are able to face a higher level of risk in order to get a higher investment return. In contrast, 3.0 and 1.5 aversion levels refer to the groups of investors that dislike risk (not risk takers) and are risk neutral, respectively.
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