Evaluating the Hedging Effectiveness in Crude Palm Oil Futures Market during Financial Crises

You-How Go
Faculty of Business and Finance, Universiti Tunku Abdul Rahman (UTAR),
Perak, Malaysia
E-mail address: goyh@utar.edu.my

Wee-Yeap Lau (Corresponding author)
Faculty of Economics and Administration, University of Malaya,
Kuala Lumpur, Malaysia.
E-mail address: wylau@um.edu.my

ABSTRACT

This study examines whether there is a significant change in hedging effectiveness on Crude Palm Oil (CPO) futures market from January 1986 to December 2013. Eight hedging models with different mean and variance-covariance specifications have been evaluated. As the volatility of spot and futures markets is not similar across time, both markets exhibit asymmetric information transmission. Our results of out-of-sample evaluation show, firstly, the time-varying hedge ratios with basis term produce better performance during both financial crises. Secondly, high dynamic hedge ratios during the Asian financial crisis contribute to the support for CCC-GARCH model. Thirdly, during global financial crisis, BEKK-GARCH model appears to provide more risk reduction as compared to others. From the perspective of economic modeling, incorporating the basis term in modeling the joint dynamics of spot and futures returns during the crises provide better results. This study recommends that CPO market participants to adjust their hedging strategies in response to different movement in market volatility.

Keywords: Generalized autoregressive conditional heterosedasticity (GARCH) model, basis term, minimum-variance hedge ratios and hedging effectiveness.
JEL Classification: G12, G13, G14

1. Introduction

Being one of the world leading producers and exporters of palm oil, Malaysia alone accounted for 39 per cent of world production and 45 per cent of world exports in 2011 based on the data released by the Malaysian Palm Oil Board (MPOB). Given the prominence of this commodity to the economy, Malaysian crude palm oil (CPO) futures market has been in existence in the Kuala Lumpur Commodity Exchange (KLCE) since October 1980, and continued to be one of the active futures market for CPO related derivative product in the world under the platform of Bursa Malaysia Derivative (BMD) Berhad in 2003.

Like other market commodities, the price movement of CPO is subjected to fluctuation throughout various economic climates. As observed in Figure 1, it shows that CPO spot and futures returns have high volatility in three distinct periods which correspond to the world economic recession in 1986, Asian financial crisis in 1997/1998 and global financial crisis in 2008/2009. Besides the global economic recession, which happened during 1985-1987, Malaysian palm oil was subject to a series of adverse publicity launched by the American Soybean Association. As a consequence, Malaysian growth was halted abruptly as palm oil price had been halved.

In the aftermath of Asian financial crisis, the depreciation of Ringgit caused the restructuring of the Malaysian derivative market to undergo a series of regulatory reform. In response to this crisis, BMD's CPO futures contracts were traded RM2,700 per tonne at the Commodity and Monetary Exchange (COMMEX) in November 1998 (MPOB, 1998). Subsequently, palm oil has become the top foreign exchange earner, exceeding the revenue derived from crude petroleum, petroleum products by a wide margin.

However, due to the La Nina effect in 2008, Malaysian palm oil export dropped from RM13, 504 million tonnes in the third quarter to RM9, 271 million tonnes in the fourth quarter of 2008 due to heavy rainfall and lower fresh fruit bunches (Central Bank Malaysia, 2009). It was observed that CPO futures price also decreased from an average of RM3506.12 in the first quarter of 2008 to RM1898.93 in first quarter of 2009. [1]

Since the revival of China and India's gross domestic production growth in 2009, the total CPO futures contract traded has subsequently increased from 3,003,549 contracts in 2008 to 4,008,882 contracts in 2009 steadily with the rising of demand from both countries.[2] After recovery in the global economy in 2010, the rising of petroleum crude oil has continually led to the increase of CPO price and directly reduced pricing volatility after 2011.

The above account testifies that the price movement of CPO is uncertain and often influenced by economic or environmental factors. Hence, to implement better hedging strategies during economic downturn, there is a need among market participants to focus on futures market as a means to minimize the risk of price fluctuation. However, there is

[1] Based on data are extracted from Thomson DataStream on 12 January 2013
[2] See the report of the United Nations Development Program (2009) at p. 68.

no conclusive evidence to state which model provides the best hedging performance during extremely volatile economic periods. This study intends to revisit this issue and extend earlier studies by using basis term in modeling the joint dynamics of spot and futures returns.

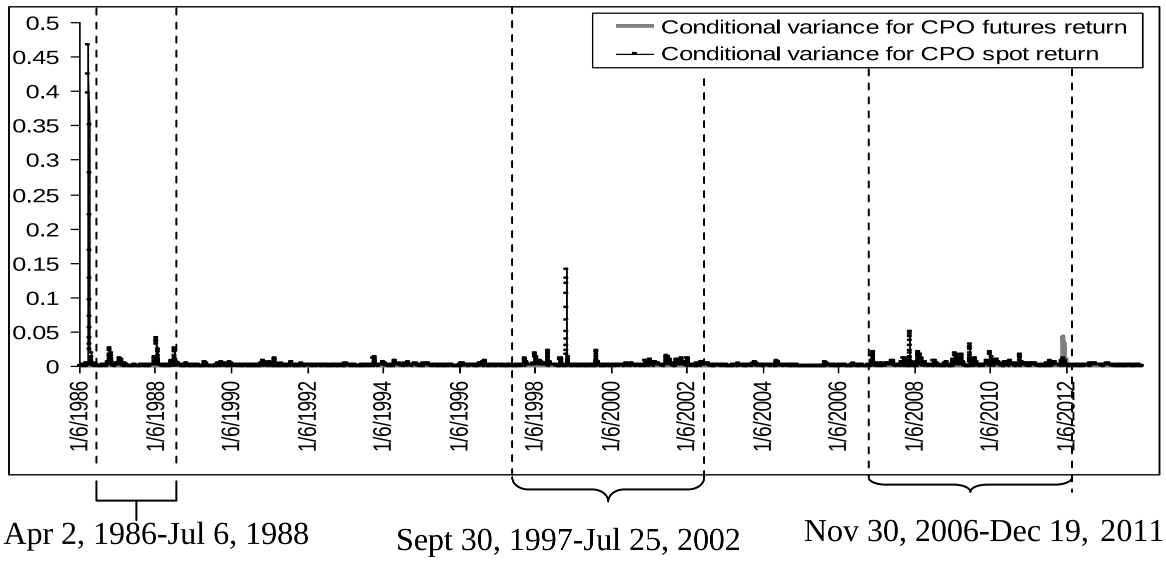

Figure 1. Univariate conditional variance of CPO spot and futures returns, 1986-2013

Source: Author's estimation based on Exponential-GARCH model of Malaysian CPO spot and futures returns

Working (1953) defines hedging as "the purchase or sale of futures in conjunction with another commitment, usually in expectation of a favorable change in the relation between spot and futures prices". On the other hand, Ederington (1979) defines that hedging effectiveness is a variance reduction in the spot return portfolio. In another study, Howard and D'Antonio (1984) define that the hedging effectiveness is the ratio between excess return per unit of risk in the portfolio of the spot and futures positions to excess return per unit of risk in the portfolio of the spot position.

There are two contributions of this study. Firstly, this study investigates whether the superior hedging model can produce asymmetric performance in reducing the variance of portfolio across three sub-periods, namely the world economic recession in 1986, Asian financial crisis in 1997/1998 and global financial crisis in 2008/2009 respectively. This assessment is important for the CPO market participants to know whether they need to adjust or switch their hedging models in mitigating price risk across different market conditions.

Secondly, this study extends the studies of Zainudin and Shaharudin (2011) and Ong, Tan and Teh (2012) on hedging effectiveness in the Malaysian CPO futures market by incorporating basis term (the short run deviation between CPO spot and futures prices) into conditional variance-covariance structures of Baba-Engle-Kraft-Kroner (BEKK) and

Constant Conditional Correlation (CCC) representations. Although the basis term has been confirmed to be a factor influencing the level of spot and futures price movements in the model, this study attempts to verify whether the basis term can sustain its superiority during highly volatile periods in generating the best hedge ratios and performance for the case of the Malaysian CPO futures market.

This paper is organized as follows. This section is followed by a literature review. The subsequent section touches on data and methodology, followed by findings and empirical results. The last section concludes the discussion and suggests the implication of this study.

2. Literature Review

2.1. Hedging model specifications

The debate on econometric models for estimating the minimum-variance futures hedge ratio has been discussed for many years. In early studies, Johnson (1960) was the first to introduce optimal hedge ratio (OHR) in minimizing portfolio variance in hedging strategies. He defined that OHR was the ratio between covariance between spot and futures returns to the variance of futures return. Stein (1961) was the first to use an ordinary least squares (OLS) method to regress the spot returns against futures returns by assuming covariance exhibited time-invariant characteristics. The estimated slope of a model could be interpreted as OHR. The high R squared from the estimated linear regression model indicated that the OLS hedging strategy was effective. This assumption was further used by Ederington (1979), Anderson and Danthine (1981) and Hill and Schneeweis (1981).

Nevertheless, Ederington (1979) found that the hedging effectiveness based on the R squared from a simple regression was inappropriate to estimate OHR because the movement of the OHR exhibited time-variant characteristics and correlation between two rates of return also varying across time. This effect leads to risk-minimizing hedge ratios to be time-varying as well. To account for this effect, a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) framework is constructed to display time-varying volatility of both returns. As a result, there have been a number of proponents for the GARCH framework with each of them demonstrated the effectiveness of dynamic hedge ratios with respect to the highest variance reduction (Baillie & Myers, 1991; Park & Switzer, 1995; Tong, 1996; Moschini & Myers, 2002; Lien, Tse & Tsui, 2002; Floros & Vougas, 2004; Ahmed, 2007; and Zainudin & Shaharudin, 2011).

To explain the conditional covariance between the spot and futures returns and estimate OHR under the time-varying framework, Bollerslev, Engle and Wooldridge (1988) have extended GARCH model to become a Bivariate GARCH (BGARCH) model. With the respect to this model, Baillie and Myers (1991) found that OHR exhibited non-stationary movement across time in the United States six commodities. This non-stationary movement implied that the assumption of a time-invariant OHR was not longer inappropriate to be used. This demonstrated that the BGARCH model appeared to fit the data well because the considerable time variation in the conditional covariance matrix.

Park and Switzer (1995) further demonstrated its superiority in the corn and soybean markets. In contrast to the evidence as demonstrated above, they found this model could not guarantee to provide the superior hedging strategy to OLS hedging strategy when volatility movement was not stable and high, and as well as the consideration of transaction cost. As a result, this model contained too many parameters and did not restrict conditional variance-covariance matrix to be a positive semidefinite.

To ensure the positive semidefinite in variance-covariance matrix, Engle and Kroner (1995) have developed the variance-covariance with BEKK (name after Baba, Engle, Kraft and Kroner) specification. Subsequently, the GARCH model with this specification was turned to be more flexible for the researchers to study hedging performance in variety commodity markets. For instance, Moschini and Myers (2002) used BEKK-GARCH model for hedging of weekly corn prices in Midwest during 1976-1997. They found that this model was the best, but it could not be used to explain deterministic seasonality and time-to-maturity effects. Floros and Vougas (2004) found the superiority of this model in capturing new information arrival in the Greek market for the period 1999-2001. Alizadeh, Kavussanos and Menachof (2004) compared hedging effectiveness across Rotterdam, Singapore and Houston during 1988-2000 using the BEKK-GARCH model. They pointed out that low hedging performance was due to different regional supply and demand of crude oil and petroleum.

As discussed by Brooks, Henry and Persand (2002), asymmetric effects of positive and negative returns cannot be neglected from BEKK parameterization in estimating hedge ratios. This could be demonstrated through the GARCH model with the asymmetric effects provided the superior hedging performance for in-sample, but its effectiveness was low for the out-of-sample. By using Fama's regression approach (1984) and simple random walk model, Switzer and El-Khoury (2007) have presented the evidence of the asymmetric effects of bad and good news in improving hedging performance in the New York Mercantile Exchange Division light sweet crude oil futures contract market from 1986 to 2005. During the period 1992-2009, Wu, Guan and Myers (2011) used the asymmetric version of the BEKK model to account for a possibly asymmetric effect of volatility. They found evidence of hedging strategy across corn and crude oil markets to be slightly efficient than traditional hedging strategy in the corn futures market alone.

As suggested by the efficient markets hypothesis, the cointegration relationship between spot and futures prices should be examined because both prices contain a stochastic trend. Kroner and Sultan (1993) were the first to adopt the GARCH framework with an error correction term in estimating dynamic hedge ratios. They found that this framework provided the superior hedging performance over more conventional hedging measures.

Subsequently, a number of researchers have adopted the GARCH with the error correction term in their studies. For instance, Tong (1996) supported the incorporating the error correction term into mean equation of BEKK-GARCH model could improve hedging performance in the Tokyo stock index during 1980-1987. Choudhry (2002, 2004) found similar results with Tong (1996), where GARCH hedging strategy with the error correction term was outperformed in the Australia, Germany, Hong Kong, Japan, South African and United Kingdom futures markets during 1990-1999. He further made investigation in the Australia, Hong Kong and Japan stock market during 1990-2000 and confirmed that this error term is crucial in the most of the cases.

The GARCH model has 11 parameters in the conditional variance-covariance structure with BEKK formulation. To obtain a parsimonious model, Bollerslev (1990) has developed the Constant Conditional Correlation (CCC)-GARCH model that consists of 7 parameters in order to provide simple computation and ensure the positive semi-definite in the conditional variance-covariance matrix (Kroner & Sultan, 1993; Ng & Pirrong, 1994; and Lien *et al* 2002). Alternative estimation of OHR supported that constant correlation between standardized residuals of spot and futures returns (residuals divided by the GARCH conditional standard deviation) provided high explanatory power to the conditional variance-covariance of both series, and hence CCC-GARCH model was preferred in view of this. Empirical research that used this model includes: Lien *et al* (2002) and Ahmed (2007).

On the contrary, Lien *et al* (2002) found that OLS estimation model was better than a CCC vector GARCH model in the currency futures, commodity futures and stock index futures during 1988-1998. Their results indicated that the underperformance of CCC-GARCH model often generated too variable forecasted variance. According to the authors, a time-varying regime-switching model has appeared to be a better model to improve the accuracy of the model in variance forecasting. Ahmed (2007) compared the effectiveness of time-varying and traditional duration-based constant hedge ratios in the United States Treasury market. His finding indicated that the estimated time-varying hedge ratio from the CCC-GARCH able to capture the conditional heteroskedasticity in the spot market. As a result, this model has provided an advantage in minimizing the variance for bond investors to change their positions in futures market based on the changes in actual yields of spot market during ten years of trading.

2.2. Hedging effectiveness in Malaysian CPO futures market

There are empirical works related to hedge ratio analysis for the case of Malaysian palm oil. For instance, Zainudin and Shaharudin (2011) claimed that the different restriction imposed in the conditional mean equation could affect the hedging effectiveness in the Malaysian CPO futures market. They used the BEKK-GARCH model with three different mean specifications comprising the intercept, Vector Autoregressive (VAR) and Vector Error Correction model (VECM) to examine hedging effectiveness based on risk minimization and utility maximization. Based on risk minimization within the in- and out-of-sample, they found that a parsimonious model such as the BEKK-GARCH models with mean intercept and VAR provided better hedging performance as compared to complicated model such as the BEKK-VECM model. The difference between tested models was small in terms of utility maximization.

In another study by Ong *et al* (2012), with an OLS method in estimating the hedge ratio for each month during 2009-2011, they reported that the increasing hedge ratio during January, 2009-June, 2011 has contributed to 19-53 per cent of the hedging effectiveness. They claimed that this low level of hedging performance was due to four events, (1) the rising of petroleum crude oil, (2) recovery of world economy in 2010, (3) weak impact of the tsunami and earthquake in Japan, and (4) debt crisis in Europe has caused stable and consistent movement of volatility in the CPO spot market.

3. Data and Methodology

This study uses daily closing CPO spot and futures prices from January 6, 1986 to December 31, 2013 which consist of 6,782 observations. The data are collected from Thomson Reuters DataStream. In order to reduce the variability of both series and achieve stationarity, both prices are transformed to returns in the natural logarithmic form. Subsequently, the whole sample period is divided into three sub-periods, the first sub - period from April 2, 1986 to July 6, 1988, the second sub - period from Sept 30, 1997 to July 25, 2002 and lastly the third sub-period from November 30, 2006-December 19, 2011.

As observed in Table 1, the lowest means of both daily returns with negative values are recorded during the Asian financial crisis. In the same period, the lowest standard deviation of 0.0190 indicates that spot market has less volatility. Across the three periods, it is observed that the standard deviation of spot and future returns slightly increased to 0.027 and 0.0267 during the global financial crisis..

Table 1. Descriptive statistics of CPO returns

	Panel A: Apr 2, 1986 – Jul 6, 1988		**Panel B: Sept 30, 1997 – Jul 25, 2002**		**Panel C: Nov 30, 2006 – Dec 19, 2011**	
	Spot	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**
Observations	549	549	1180	1180	1241	1241
Mean	0.0004	0.0011	-4.88E-05	-6.56E-05	0.0004	0.00037
Std deviation	0.0279	0.0211	0.0190	0.0252	0.027	0.0267
Maximum	0.1915	0.0729	0.0975	0.3569	0.211	0.4217
Minimum	-0.3867	-0.0798	-0.0778	-0.1511	-0.3020	-0.4038
Skewness	-4.3620	0.0778	0.3294	2.0373	-2.4272	0.2242
Kurtosis	79.7350	4.268	4.974	43.1774	42.6643	94.2995
Jarque-Bera	136435.3*	37.33*	212.91*	80182.10*	82569.07*	431029.9*

Note: * indicates null hypothesis is rejected at the 1% level.

Based on Table 2, augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test statistics support the rejection of null hypotheses of a unit root, implying the unit root is absence for daily CPO spot and futures returns series. Therefore, both returns are stationary in level form. Furthermore, various models with different mean and variance specifications are estimated in each sub-period. Subsequently, the in- and out-of-sample performance for each model is compared to examine asymmetric performance of hedging across the three events.

Table 2: Unit root test results

		CPO Spot	CPO Futures
Augmented Dickey-Fuller (ADF)	Drift	-85.5402*	-87.8223*
	Drift and Trend	-85.5339*	-87.8165*
Phillips-Perron (PP)	Drift	-85.5057*	-87.9983*
	Drift and Trend	-85.4994*	-87.9928*

Notes: Null hypothesis states that the existences of unit root in returns. * indicates null hypothesis is rejected at the 1% level.

3.1 Model specifications

This study involves three-step approach. The first step to estimate Minimum-Variance Optimal Hedge Ratio (MVOHR) by using time-varying and time-invariant hedging models. Second step is to compute variance of the portfolio, and finally, we proceed to evaluate the hedging effectiveness using the minimum variance framework in each sub-period.

Two types of time-invariant hedging models are used in this study, namely naïve and Ordinary Least Squares (OLS). However, if conditional variance-covariance matrix is time-variant, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model will be used to estimate OHR. Two versions of GARCH models i.e Baba-Engle-Kraft-Kroner (BEKK) and Constant Conditional Correlation (CCC) representation are used in this study.

3.1.1 Mean specifications

In the time-varying framework, we estimate three types of conditional mean specifications. First, this study considers a simple mean model as follows:

$$r_{S,t} = c_S + \varepsilon_{S,t} \;;\; \varepsilon_{S,t} \big| \Omega_{t-1} \sim N(0, H_t) \quad (1)$$

$$r_{F,t} = c_F + \varepsilon_{F,t} \;;\; \varepsilon_{F,t} \big| \Omega_{t-1} \sim N(0, H_t) \quad (2)$$

where $r_{S,t}$ = daily CPO spot return at time t

$r_{F,t}$ = daily CPO futures return at time t

$\varepsilon_{S,t}$ = unexpected daily CPO spot return that cannot be predicted based on all information about daily CPO spot return available up to the preceding period

$\varepsilon_{F,t}$ = unexpected daily CPO futures return that cannot be predicted based on all information about daily CPO future return available up to the preceding period

Ω_{t-1} = information set available to time $t-1$

H_t = conditional variance of daily CPO spot and futures returns at time t respectively

Second, we model the conditional mean equation by considering both CPO returns lagged term $(r_{S,t-i}, r_{F,t-i})$ to capture the short run association between CPO spot and futures returns. Hence, vector autoregressive (VAR) mean modeling is specified as follows:

$$r_{S,t} = c_S + \sum_{i-1}^{k} a_{S,i} r_{S,t-i} + \sum_{i=1}^{k} b_{S,i} r_{F,t-i} + \varepsilon_{S,t} \;;\; \varepsilon_{S,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{3}$$

$$r_{F,t} = c_F + \sum_{i-1}^{k} a_{F,i} r_{S,t-i} + \sum_{i=1}^{k} b_{F,i} r_{F,t-i} + \varepsilon_{F,t} \;;\; \varepsilon_{F,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{4}$$

Third, we include a lagged one of basis (Z_{t-1}) to measure the long-run relationship between the CPO spot and futures prices. For the conditional mean equation, this study follows model specification by Lien and Yang (2008).[3] Both conditional means of CPO spot and futures returns are written as equations (5) and (6).

$$r_{S,t} = c_S + \sum_{i=1}^{k} a_{S,i} r_{S,t-i} + \sum_{i=1}^{k} b_{S,i} r_{F,t-i} + \eta_S Z_{t-1} + \varepsilon_{S,t} \quad ;\; \varepsilon_{S,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{5}$$

$$r_{F,t} = c_F + \sum_{i=1}^{k} a_{F,i} r_{S,t-i} + \sum_{i=1}^{k} b_{F,i} r_{F,t-i} + \eta_F Z_{t-1} + \varepsilon_{F,t} \quad ;\; \varepsilon_{F,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6}$$

In equations (5) and (6), Z_{t-1} is measured by $(\ln P_{S,t-1} - \ln P_{F,t-1})$, where $\ln P_{S,t-1}$ and $\ln P_{F,t-1}$ are denoted as daily CPO spot and futures prices in natural logarithmic form at time $t-1$ respectively. A negative basis indicates that futures price exceeds spot price at time $t-1$. In order to eliminate a deviation from the long run relationship between both prices, the futures price tends to decease whereas the spot price tends to increase at time t. This leads to $\eta_S \geq 0$ and $\eta_F \leq 0$, as well as at least one of parameter is nonzero. Otherwise, it is for a positive basis.

3.1.2 Variance-covariance specifications

If conditional variance-covariance has a time-varying structure, GARCH (1,1) model is used. To maintain positive semidefinite of the estimated parameters in the variance-covariance structure, we adopt the two different specifications of conditional variance-covariance.

[3] Refer to Lien and Yang (2008) at pp.126.

First specification of time-variant model is a general BEKK-GARH (1,1) model (Engle & Kroner, 1995), where H_t is defined as follows:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + GH_{t-1}G'$$

$$H_t = \begin{bmatrix} H_{SS} & H_{SF} \\ H_{FS} & H_{FF} \end{bmatrix}; C = \begin{bmatrix} C_{SS} & C_{SF} \\ 0 & C_{FF} \end{bmatrix}; A = \begin{bmatrix} A_{SS} & A_{SF} \\ A_{FS} & A_{FF} \end{bmatrix}; \quad G = \begin{bmatrix} G_{SS} & G_{SF} \\ G_{FS} & G_{FF} \end{bmatrix}; \quad \text{and}$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix}.$$

$$h_{SS,t} = C_{SS} + A_{SS}\varepsilon^2_{S,t-1} + G_{SS}h_{SS,t-1}$$

$$h_{FF,t} = C_{FF} + A_{FF}\varepsilon^2_{F,t-1} + G_{FF}h_{FF,t-1}$$

$$h_{SF,t} = C_{SF} + A_{SF}\varepsilon_{S,t-1}\varepsilon_{F,t-1} + G_{SF}h_{SS,t-1}h_{FF,t-1} \quad (7)$$

where $H_t =$ conditional covariance matrix at time t

C = constant coefficient parameters for daily CPO spot and futures returns respectively

A = squared error lagged coefficient parameters for daily CPO spot and futures returns respectively

G = volatility lagged coefficient parameters for daily CPO spot and futures returns respectively

ε_t = error terms for daily CPO spot and futures returns respectively

$h_{SS,t}$ = conditional variance of daily CPO spot return at time t

$h_{FF,t}$ = conditional variance of daily CPO futures return at time t

$h_{SF,t}$ = conditional covariance at time t

Based on equation (7), the BEKK parameterization requires estimation of 11 parameters in the conditional variance-covariance structure. This specification assumes that spillover parameters are constant $(A_{SF} = A_{FS}, G_{SF} = G_{FS})$ throughout the entire sample periods without taking correlation into account. [4] With less number of parameters, this model maintains the positive semidefinite of estimated parameters for conditional variance and covariance. This condition can be satisfied by imposing parameter constraints of "$0 < (A+G) \leq 1$".

The second specification of the time-variant model is a CCC-GARCH (1,1) of which is estimated by taking standardized residuals of spot and futures returns (residuals divided by the GARCH conditional standard deviation) into conditional correlation matrix (ρ) (Bollerslev,1990). Based on this model, the conditional correlation is assumed to be time-invariant. Subsequently, H_t is defined as follows:

$H_t = D_t R D_t$, where $D_t = diag\{\sqrt{h_{i,t}}\}$

[4] Refer to article of Wu *et al* (2011) from pp.1056 to 1063.

$$= Var\left(\varepsilon_{S,t}, \varepsilon_{F,t} | \phi_{t-1}\right) \equiv \begin{bmatrix} h_{SS,t} & h_{SF,t} \\ h_{FS,t} & h_{FF,t} \end{bmatrix} = \begin{bmatrix} \sqrt{h_{SS,t}} & 0 \\ 0 & \sqrt{h_{FF,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{SS,t}} & 0 \\ 0 & \sqrt{h_{FF,t}} \end{bmatrix}$$

$$h_{SS,t} = \omega_{SS} + \alpha_{SS}\varepsilon^2_{S,t-1} + \beta_{SS} h_{SS,t-1}$$

$$h_{FF,t} = \omega_{FF} + \alpha_{FF}\varepsilon^2_{F,t-1} + \beta_{FF} h_{FF,t-1}$$

$$h_{SF,t} = \rho\sqrt{h_{SS,t} h_{FF,t}}$$

$$\rho = E_{t-1}\left(\eta_t \eta'_t\right) = D_t^{-1} H_t D_t^{-1}, \eta_t = \frac{\varepsilon_t}{\sqrt{h_t}} \tag{8}$$

where H_t = conditional covariance matrix at time t

R = correlation matrix of standardized residuals for daily CPO spot and futures returns

$h_{SS,t}$ = conditional variance of daily CPO spot return at time t

$h_{FF,t}$ = conditional variance of daily CPO futures return at time t

$h_{SF,t}$ = conditional covariance at time t

ρ = correlation coefficient between standardized residuals of daily CPO spot and futures returns

Past studies have used the CCC-GARCH model because it is a parsimonious model with 7 parameters that provides simple computation (see Kroner & Sultan, 1993; Ng & Pirrong, 1994; and Lien *et al* 2002). Based on equation (8), a positive semidefinite of the conditional variance-covariance matrix is guaranteed by assuring $h_{SS,t} > 0$ and $h_{FF,t} > 0$, where $\omega > 0, \alpha > 0, \beta > 0$, and $0 < \alpha + \beta \le 1$ for individual GARCH (1,1) process.

According to Ng and Pirrong (1994), size of basis affects price volatility in the energy futures market. This implies that spot and futures markets are more volatile when the size of basis is large, suggesting arbitrage activities are ineffective. Kogan, Livdan and Yaron (2003) predict that the volatility of spot or futures returns and the basis have a V-shape effect. To capture the effect of the short run deviation between both prices on the conditional variance-covariance (H_t), the lagged one of basis squared is included into H_t equation that follows BEKK and CCC settings to become equation (9) as follows:

$$h_{k,t} = \omega_k + \alpha_k \varepsilon^2_{k,t-1} + \beta_k h_{k,t-1} + \theta_k \left(Z_{t-1}\right)^2 \text{ for } k = SS, FF, SF \tag{9}$$

The estimation of all GARCH models above is carried out by maximizing value of log-likelihood using equation (10) as follows:

$$L(\theta) = -T\ln(2\pi) - (1/2)\sum_{t=1}^{T}\left(\ln\left|H_t(\theta)\right| + \varepsilon_t(\theta) H_t^{-1}(\theta)\varepsilon_t'(\theta)\right) \tag{10}$$

3.2 Minimum-variance hedge ratio (MVHR) estimation

The MVHR at a point in time $\left(h_t \middle| \Omega_{t-1}\right)$ is then calculated using equation (11) as a ratio of the conditional covariance between spot and futures $\left(h_{SF,t}\right)$ to the conditional variance of futures $\left(h_{FF,t}\right)$. The obtained MVHRs from the BEKK- and CCC-GARCH (1,1) models are used to calculate variance of portfolio and hedging effectiveness.

$$h_t \middle| \Omega_{t-1} = \left(\frac{h_{SF,t}}{h_{FF,t}}\right) \middle| \Omega_{t-1} \quad (11)$$

3.3 Variance of portfolio

In the time-varying analysis, variance of portfolio $\left(H_{p,t}\right)$ is calculated by substituting dynamic MVHR (from equation (11)), conditional variance in the CPO spot market, conditional variance in the CPO futures market and conditional covariance of both CPO returns into equation (12).

$$H_{p,t} = h_{SS,t} + \left(h_t \middle| \Omega_{t-1}\right)^2 h_{FF,t} - 2\left(h_t \middle| \Omega_{t-1}\right) h_{SF,t} \quad (12)$$

3.4 Hedging performance measurement

The last step is to evaluate the hedging effectiveness for time-invariant and time-variant models based on risk minimization context, where it is the most frequently used as the hedging performance measure. According to Ederington (1979), the risk minimization is measured using equation (13) to compute the percentage of variance reduction in adjusting hedging strategy. The hedging strategy is effective if the variance of return on a hedged portfolio (refer to equation (12)) approximately equal to zero as compared to unhedged portfolio.

$$\text{Percentage of variance reduction} = \frac{H_{p,t}(Unhedged) - H_{p,t}(Hedged)}{H_{p,t}(Unhedged)} \times 100 \quad (13)$$

where $H_{p,t}(Unhedged)$ = variance of portfolio from an unhedged strategy or unconditional variance of daily CPO spot return

$H_{p,t}(Hedged)$ = variance of portfolio from a hedging strategy (refer to equation (12))

4. Results

4.1 BEKK and CCC estimations with different mean and variance-covariance specifications

First of all, the BEKK- and CCC-GARCH models with different mean and variance specifications are estimated in each sub-period. The estimated results for these models are summarized in Table 3 and Table 4 respectively.

From Table 3, it is observed that the variances of CPO spot and futures returns with BEKK framework are highly influenced by their own past squared residuals (A_{SS}

and A_{FF}) and own past variances (G_{SS} and G_{FF}) in the most of cases. Most of the coefficients of A_{SF} and G_{SF} in covariance equations are found as significant, indicating the volatility in both markets exhibit interactive effect. The coefficients of η_S and η_F in the conditional mean equation are significant in the most of sub-periods, whereas the coefficients of θ_{SS}, θ_{FF} and θ_{SF} are majority insignificant in the variance-covariance equations, especially during the Asian financial crisis (Panel B). This implies that incorporating lagged one of basis is crucial in modelling the conditional mean instead of the variance-covariance.

As observed in Table 4, the constant conditional correlation assumption provides the significant coefficients of α_{SS} and α_{FF} in the most of sub-periods. This reveals the past squared residuals have an effect on the conditional variance of spot and futures. Similar finding has been found for the coefficient of β_{SS}. For the coefficient of β_{FF}, it indicates that the past variance of futures market insignificantly affects its own current variance in the most of cases during the Asian financial crisis (Panel B). The coefficient of η_S is found to be highly significant as compared to η_F, indicating the lagged one of basis has an explanatory power in describing the conditional mean of spot market instead of futures market. Both coefficients of θ_{FF} and θ_{SF} indicate that the basis term contributes significant effect on either the conditional variance of spot or futures markets in Panel A and Panel B, but this term is found to have a significant effect on both markets in Panel C. Furthermore, the constant conditional correlations between standardized residual of spot and futures returns are found to be the strongest during the Asian financial crisis (Panel B). These correlations are found to be weak in the subsequent crisis (Panel C).

For diagnostic testing, Ljung–Box statistics of the 15th order are presented in Table 3 and Table 4. These statistics are based on standardized residuals and their squares, implying there is no need to encompass a higher order ARCH process (Giannopoulos, 1995). In Panel A, it indicates that VAR-BEKK-GARCH model free from serial correlation and ARCH problems in both residual series. Subsequently, in Panel B and Panel C, the GARCH models with the short run and long run relationships of both series have no serial correlation in the standardized residuals and the standardized squared residuals as compared to the intercept-GARCH model. Based on these estimated models, the minimum-variance hedge ratios are constructed and its descriptive statistics for the in- and out-of- sample analysis are reported in Table 5.

Table 3: The estimation results of BEKK-GARCH (1,1) model by using maximum likelihood during the whole period

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional mean equation:									
c_S	0.0011 (0.001)	0.0002 (0.0011)	0.0163*** (0.0011)	-0.0004 (0.0005)	-0.0004 (0.0005)	0.0005 (0.0006)	0.0006 (0.0008)	0.0007 (0.0008)	0.0056*** (0.001)
$a_{S,1}$	-	-0.1128 (0.0925)	-0.1483 (0.0971)	-	0.0228 (0.0311)	0.0130 (0.0313)	-	-0.102*** (0.0335)	-0.0690** (0.0309)
$a_{S,2}$	-	-0.0198 (0.04)	-0.0362 (0.0505)	-	-	-	-	-	-
$a_{S,3}$	-	-0.0193 (0.0481)	-0.02 (0.0517)	-	-	-	-	-	-
$a_{S,4}$	-	-0.0112 (0.0494)	0.0748*** (0.0233)	-	-	-	-	-	-
$b_{S,1}$	-	0.1107** (0.0549)	0.0061 (0.0329)	-	0.0216 (0.0162)	0.026 (0.0168)	-	0.0838*** (0.0160)	0.0238 (0.0248)
$b_{S,2}$	-	0.0668* (0.0393)	0.1361*** (0.0316)	-	-	-	-	-	-
$b_{S,3}$	-	0.2113*** (0.0443)	0.1084*** (0.0371)	-	-	-	-	-	-
$b_{S,4}$	-	0.2654*** (0.0474)	0.1315*** (0.0326)	-	-	-	-	-	-
η_S	-	-	-0.1595*** (0.0129)	-	-	-0.0073** (0.0038)	-	-	-0.0703** (0.0124)
c_F	0.0007 (0.0008)	0.0007 (0.0007)	0.0039** (0.0016)	-0.0003 (0.0008)	-0.0002 (0.0007)	0.0025** (0.0011)	0.0022*** (0.0005)	0.0023*** (0.0004)	0.003*** (0.0007)
$a_{F,1}$	-	0.1434*** (0.0318)	0.1276*** (0.0263)	-	0.358*** (0.0361)	0.3534*** (0.0391)	-	-0.0246 (0.0166)	-0.018 (0.0167)
$a_{F,2}$	-	0.0250 (0.031)	0.0277 (0.0270)	-	-	-	-	-	-
$a_{F,3}$	-	0.0982*** (0.0345)	0.1018*** (0.0337)	-	-	-	-	-	-
$a_{F,4}$	-	0.0185 (0.0391)	0.0755** (0.0344)	-	-	-	-	-	-
$b_{F,1}$	-	0.1194** (0.0482)	0.1085** (0.0487)	-	-0.1431*** (0.04)	-0.1473*** (0.0407)	-	-0.0614 (0.0429)	0.0777* (0.0449)
$b_{F,2}$	-	-0.0703 (0.0447)	-0.0498 (0.0443)	-	-	-	-	-	-
$b_{F,3}$	-	0.0278 (0.0476)	0.0188 (0.0473)	-	-	-	-	-	-
$b_{F,4}$	-	0.0757* (0.0441)	0.0625 (0.0456)	-	-	-	-	-	-
η_F	-	-	-0.0297* (0.0156)	-	-	-0.0259** (0.011)	-	-	-0.0113 (0.0078)

Table 3: (Continued)

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional variance-covariance equation:									
C_{SS}	0.0001***	1.28E-05**	2.53E-05*	7.50E-06***	1.2E-05***	1.30E-05***	0.0002***	0.0002***	0.0004***
	(1.41E-05)	(5.03E-06)	(1.38E-05)	(1.77E-06)	(2.7E-06)	(2.87E-06)	(2.5E-05)	(2.94E-05)	(1.60E-05)
C_{FF}	1.57E-05***	1.72E-05**	1.50E-05*	7.2E-06**	0.0001***	0.0001**	8.8E-05***	8.60E-05***	5.05E-05***
	(5.64E-06)	(8.00E-06)	(7.87E-06)	(2.94E-06)	(5.03E-05)	(4.29E-05)	(1.22E-05)	(1.21E-05)	(1.21E-05)
C_{SF}	1.80E-05**	6.84E-06**	9.97E-06	6.16E-06***	1.93E-05***	1.80E-05***	2.9E-05***	2.92E-05***	0.0001***
	(7.44E-06)	(2.80E-06)	(8.02E-06)	(1.11E-06)	(5.89E-06)	(5.54E-06)	(7.67E-06)	(7.71E-06)	(1.59E-05)
A_{SS}	-0.0023	-0.0842***	0.7636***	0.2806***	0.3321***	0.3327***	0.2271***	0.217***	0.2754***
	(0.0723)	(0.016)	(0.0665)	(0.0175)	(0.023)	(0.0231)	(0.0206)	(0.0231)	(0.0287)
A_{FF}	0.3891***	0.3857***	0.3379***	0.0489***	0.1370***	0.1492***	0.8108***	0.818***	0.8353***
	(0.0472)	(0.0497)	(0.0412)	(0.0116)	(0.0227)	(0.0262)	(0.0179)	(0.02)	(0.0213)
A_{SF}	-0.0009	-0.0325***	0.2581***	0.0137***	0.0455***	0.0496***	0.1842***	0.1775***	0.23***
	(0.0034)	(0.0008)	(0.0027)	(0.0002)	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0006)
G_{SS}	0.8455***	0.9827***	0.6443***	0.9477***	0.9244***	0.9223***	0.7996***	0.8123***	0.1079
	(0.0159)	(0.00672)	(0.0318)	(0.0065)	(0.01)	(0.0103)	(0.0252)	(0.0291)	(0.147)
G_{FF}	0.9002***	0.9010***	0.9258***	0.9933***	0.8806***	0.883***	0.642***	0.6421***	0.5078***
	(0.0231)	(0.0265)	(0.0189)	(0.0026)	(0.0506)	(0.0467)	(0.0224)	(0.0223)	(0.039)
G_{SF}	0.7611***	0.8854***	0.5965***	0.9414***	0.8141***	0.8144***	0.5133***	0.5215***	0.0578***
	(0.0004)	(0.0002)	(0.0006)	(1.73-E05)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0057)
θ_{SS}	-	-	0.0052***	-	-	1.30E-06	-	-	0.0149***
			(0.0009)			(2.80E-05)			(0.0011)
θ_{FF}	-	-	1.46E-05	-	-	0.0003	-	-	0.0031***
			(0.0002)			(0.004)			(0.001)
θ_{SF}	-	-	0.0003	-	-	-1.85E-05	-	-	-0.0006
			(0.0006)			(4.38E-05)			(0.001)
L	2689.764	2743.990	2791.973	5856.259	5889.206	5908.266	5773.347	5778.103	5943.883
Test for higher order ARCH effect									
Spot equations:									
$Q(15)$	22.983*	21.807	58.080***	28.979**	21.041	15.749	22.164*	15.906	15.221
$Q^2(15)$	27.300**	13.555	48.585***	28.875**	20.214	20.793	19.411	18.241	6.2956
Futures equations:									
$Q(15)$	43.711***	10.570	41.047***	12.185	10.904	12.173	19.614	23.485*	20.023
$Q^2(15)$	12.843	19.730	15.437	1.0329	0.9280	0.6505	0.8195	0.8976	0.9668

Notes: 1. (a) Intercept-BEKK-GARCH models are estimated by equations (1), (2), and (7). (b) Vector autoregressive (VAR)-BEKK-GARCH models are estimated by equations (3), (4) and (7). (c) Basis-BEKK-GARCH models are estimated by equations (5), (6) and (9). 2. *, ** and *** indicate the statistical significance at the 10%, 5% and 1% levels respectively. 3. Numbers in parentheses are the standard errors. 4. L is the value of the log-likelihood function calculated by equation (10). 5. Q and Q^2 are the Ljung–Box statistics of standardized residuals and standardized squared residuals.

Table 4: The estimation results of CCC-GARCH (1,1) model by using maximum likelihood during whole period

	Panel A: Apr 2, 1986 - Jul 6, 1988			**Panel B: Sept 30, 1997- Jul 25, 2002**			**Panel C: Nov 30, 2006 - Dec 19, 2011**		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional mean equation:									
c_S	0.0010 (0.0013)	0.0006 (0.0011)	0.0133*** (0.0008)	-0.0003 (0.0004)	-0.0003 (0.0005)	0.0006 (0.0006)	0.0009 (0.0008)	0.0009 (0.0008)	0.0063*** (0.0009)
$a_{S,1}$	-	-0.0547 (0.0348)	-0.0604*** (0.0036)	-	0.0261 (0.0314)	0.0151 (0.0322)	-	-0.140*** (0.0426)	-0.0851** (0.0396)
$a_{S,2}$	-	-0.0464 (0.0441)	-0.053*** (0.0207)	-	-	-	-	-	-
$a_{S,3}$	-	-0.0271 (0.0570)	-0.0065 (0.0242)	-	-	-	-	-	-
$a_{S,4}$	-	-0.0318 (0.0529)	0.0973*** (0.0101)	-	-	-	-	-	-
$b_{S,1}$	-	0.0982* (0.0529)	-0.0224 (0.0200)	-	0.0177 (0.0168)	0.0279 (0.0219)	-	0.1268*** (0.0187)	0.0345 (0.0278)
$b_{S,2}$	-	0.0846** (0.0360)	0.1005*** (0.0184)	-	-	-	-	-	-
$b_{S,3}$	-	0.2187*** (0.0408)	0.1149*** (0.0211)	-	-	-	-	-	-
$b_{S,4}$	-	0.245*** (0.0455)	0.1307*** (0.0209)	-	-	-	-	-	-
η_S	-	-	-0.131*** (0.0077)	-	-	-0.0071** (0.0035)	-	-	-0.0741*** (0.0112)
c_F	0.0007 (0.0008)	0.0007 (0.0007)	0.0022 (0.0018)	5.16E-05 (0.001)	-0.0001 (0.0008)	0.002* (0.0011)	0.0024*** (0.0005)	0.0025 (0.0005)	0.0033*** (0.0007)
$a_{F,1}$	-	0.16092*** (0.0407)	0.1437*** (0.0296)	-	0.3582*** (0.0355)	0.3131*** (0.0365)	-	-0.0223 (0.0183)	-0.0116 (0.0175)
$a_{F,2}$	-	0.0289 (0.0309)	0.0341 (0.0358)	-	-	-	-	-	-
$a_{F,3}$	-	0.0949** (0.0371)	0.1046*** (0.0324)	-	-	-	-	-	-
$a_{F,4}$	-	0.0354 (0.0399)	0.0535 (0.0403)	-	-	-	-	-	-
$b_{F,1}$	-	0.1126 ** (0.0487)	0.1008* (0.0542)	-	-0.129*** (0.0421)	-0.0493** (0.0218)	-	-0.0422 (0.0431)	-0.0665 (0.0453)
$b_{F,2}$	-	-0.0678 (0.0456)	-0.0602 (0.0472)	-	-	-	-	-	-
$b_{F,3}$	-	0.0191 (0.0472)	0.0105 (0.0504)	-	-	-	-	-	-
$b_{F,4}$	-	0.0656 (0.0439)	0.0567 (0.0453)	-	-	-	-	-	-
η_F	-	-	-0.015 (0.017)	-	-	-0.0162* (0.0092)	-	-	-0.0146* (0.0077)

Table 4: (Continued)

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional variance-covariance equation:									
ω_{SS}	0.0003 ***	0.0002 *	7.47E-05***	9.2E-06***	9.11E-10***	9.91E-06***	0.0002***	0.0002***	0.0004***
	(1.10E-05)	(0.0001)	(1.14E-05)	(2.36E-06)	(2.33E-06)	(2.53E-06)	(2.46E-05)	(2.8E-05)	(1.82E-05)
ω_{FF}	1.65E-05**	1.72E-05**	1.89E-05**	0.0004	0.0003*	1.25E-05	8.2E-05***	8.2E-05***	0.0001***
	(2.3289)	(8.23E-06)	(9.63E-06)	(0.0003)	(0.0002)	(3.58E-06)	(1.21E-05)	(1.19E-05)	(1.63E-05)
α_{SS}	-0.02***	-0.0137	1.4911***	0.1198***	0.1135***	0.1159***	0.0573***	0.0613***	0.101***
	(0.0005)	(0.0157)	(0.0304)	(0.0163)	(0.0154)	(0.0158)	(0.0104)	(0.0136)	(0.0216)
α_{FF}	0.15***	0.161***	0.1698***	-0.007***	0.0169	-0.0038***	0.6499***	0.6327***	0.6908***
	(0.0369)	(0.041)	(0.0437)	(0.0001)	(0.0116)	(0.0003)	(0.0332)	(0.0466)	(0.0395)
β_{SS}	0.58***	0.4984*	-0.004***	0.8584***	0.8642***	0.8607***	0.6322***	0.6501***	-0.0132
	(0.0131)	(0.2767)	(0.0012)	(0.0178)	(0.0170)	(0.0176)	(0.04)	(0.0366)	(0.0373)
β_{FF}	0.81***	0.801***	0.7887***	0.5204	0.3978	0.9811***	0.4208***	0.4213***	0.2617***
	(0.0411)	(0.0505)	(0.0524)	(0.4224)	(0.3306)	(0.0063)	(0.0294)	(0.0296)	(0.0403)
θ_{SS}	-	-	0.0062***	-	-	-1.34E-05	-	-	0.0147***
			(0.0008)			(1.97E-05)			(0.0011)
θ_{FF}	-	-	-2.40E-05	-	-	2.51E-05***	-	-	0.0029***
			(0.0004)			(6.49E-06)			(0.001)
Conditional correlation equation:									
ρ	0.103**	0.118 ***	0.1260**	0.2982***	0.3480***	0.3444***	0.0554*	0.0621**	0.0696**
	(0.0439)	(0.0441)	(0.0492)	(0.0299)	(0.026)	(0.0267)	(0.0301)	(0.0316)	(0.0315)
L	2687.813	2741.790	2837.206	5827.343	5880.906	5900.151	5767.511	5776.375	5941.987
Test for higher order ARCH effect									
Spot equations									
$Q(15)$	24.064*	18.205	60.143***	27.295**	21.650	15.922	22.116	15.744	15.473
$Q^2(15)$	26.183***	22.914*	40.009***	20.195	20.754	21.448	17.750	14.262	5.9678
Futures equations									
$Q(15)$	43.758***	11.073	11.982	13.2	11.458	15.837	18.966	21.788	18.462
$Q^2(15)$	12.848	18.961	19.560	1.2405	0.9177	2.2377	0.8527	0.9040	0.9922

Notes: 1. (a) Intercept-CCC-GARCH models are estimated by equations (1), (2) and (8). (b) Vector autoregressive (VAR)-CCC-GARCH models are estimated by equations (3), (4) and (8). (c) Basis-CCC-GARCH models are estimated by equations (5), (6) and (9). 2. *, ** and *** indicate the statistical significance at the 10%, 5% and 1% levels respectively. 3. Numbers in parentheses are the standard errors.4. L is the value of the log-likelihood function calculated by equation (10). 5. Q and Q^2 are the Ljung–Box statistics of standardized residuals and standardized squared residuals.

4.2 Impact of structural change on estimated minimum-variance hedge ratio (MVHR)

The summary of results in Table 5 indicates that means of hedge ratios are changing significantly over the three sub-periods. On average, the high optimal hedge ratios are found during the Asian financial crisis (Panel B) for about 0.5 (in-sample) and 0.3 (out-of-sample). Furthermore, the OLS hedge ratio is found to be similar to GARCH hedge ratios implying hedging effectiveness of CPO futures contract based on OLS and GARCH strategies could be very comparable during the Asian financial crisis.

As observed, hedge ratios estimated by GARCH models for out-of-sample period in Panel B show higher standard deviations as compared to other sub-periods. This implies that hedgers need to make a higher adjustment in the hedge ratio during the Asian financial crisis as compared to the global financial crisis. In summary, the impact of the Asian financial crisis on hedge ratios is the largest among the three crises.

Table 5: Summary statistics of hedge ratios

Hedge strategy	In-sample		Out-of-sample	
	Mean	SD	Mean	SD
Panel A: Apr 2, 1986 - Jul 6, 1988				
Naïve hedge	1	NA	1	NA
OLS hedge	0.1316	0.0709	0.1137	0.0874
Intercept-BEKK-GARCH hedge	0.2248	0.1037	0.0628	0.1146
VAR- BEKK-GARCH hedge	0.1968	0.0946	0.0431	0.0677
Basis-BEKK-GARCH hedge	0.1718	0.4466	-0.0255	0.0251
Intercept-CCC-GARCH hedge	0.1474	0.0424	0.0836	0.0265
VAR-CCC-GARCH hedge	0.1612	0.0408	0.0777	0.0274
Basis-CCC-GARCH hedge	0.1677	0.1308	0.0321	0.038
Panel B: Sept 30, 1997 - Jul 25, 2002				
Naïve hedge	1	NA	1	NA
OLS hedge	0.4859	0.0417	0.3332	0.0730
Intercept-BEKK-GARCH hedge	0.5333	0.2601	0.3680	0.1639
VAR- BEKK-GARCH hedge	0.5221	0.2156	0.3929	0.1805
Basis -BEKK-GARCH hedge	0.5216	0.2098	0.3776	0.1633
Intercept-CCC-GARCH hedge	0.5462	0.1595	0.3637	0.0681
VAR-CCC-GARCH hedge	0.5546	0.1591	0.3969	0.1187
Basis -CCC-GARCH hedge	0.537	0.1478	0.3831	0.1072
Panel C: Nov 30, 2006 - Dec 19, 2011				
Naïve hedge	1	NA	1	NA
OLS hedge	0.0385	0.0396	-0.0785	0.0360
Intercept-BEKK-GARCH hedge	0.223	0.2046	0.1771	0.1664
VAR- BEKK-GARCH hedge	0.2421	0.1951	0.1592	0.0958
Basis-BEKK-GARCH hedge	0.1619	0.1352	-0.1538	0.1102
Intercept-CCC-GARCH hedge	0.1335	0.0453	0.0656	0.0310
VAR-CCC-GARCH hedge	0.1472	0.0499	0.1156	0.0683
Basis -CCC-GARCH hedge	0.1446	0.0413	-0.2099	0.167

Notes: Ordinary least squares (OLS) hedge ratio is a slope of regression by regressing spot return against futures return. The BEKK- and CCC-GARCH hedge ratios are calculated by equation (11). SD is denoted as standard deviation. The SD of the naïve hedge is not available as the ratio remains constant over time. The SD of OLS hedge ratio is a standard error of a slope for futures return.

4.3 Impact of structural change on hedging effectiveness

Table 6 reports the variance of portfolio and variance reduction for unhedged and hedged returns produced by naïve, minimum variance-OLS and various GARCH hedging models.

Table 6: Hedging effectiveness of Malaysian CPO futures

Hedge strategy	In-sample		Out-of-sample	
	Variance of portfolio	Variance reduction (%)	Variance of portfolio	Variance reduction (%)
Panel A: Apr 2, 1986 - Jul 6, 1988				
Unhedged CPO portfolio	0.000819	-	0.000627	-
Hedged CPO portfolio:				
Naïve hedge	0.0010908	-33.19068	0.001211	-93.1138
OLS hedge	0.0008126	0.78056	0.000617	1.558
Intercept-BEKK-GARCH hedge	0.0005952	27.3264	0.000618	1.53
VAR-BEKK-GARCH hedge	0.0004022	50.8849	0.000545	13.044
Basis -BEKK-GARCH hedge	0.000621	24.132	0.001863	-197.079
Intercept-CCC-GARCH hedge	0.0007065	13.7282	0.00063	-0.4026
VAR-CCC-GARCH hedge	0.000409	50.114	0.000554	11.624
Basis-CCC-GARCH hedge	0.0007	14.513	0.001806	-187.9868
Panel B: Sept 30, 1997 - Jul 25, 2002				
Unhedged CPO portfolio	0.000653	-	0.00056	-
Hedged CPO portfolio:				
Naïve hedge	0.000663	-1.0504	0.000698	-24.553
OLS hedge	0.000571	12.612	0.000514	8.176
Intercept-BEKK-GARCH hedge	0.000545	16.504	0.000495	11.622
VAR-BEKK-GARCH hedge	0.000554	15.216	0.000339	39.506
Basis -BEKK-GARCH hedge	0.000564	13.574	0.000316	43.655
Intercept-CCC-GARCH hedge	0.000764	17.0479	0.000512	8.554
VAR-CCC-GARCH hedge	0.00055	15.798	0.000384	31.38
Basis-CCC-GARCH hedge	0.000539	17.476	0.000307	45.146
Panel C: Nov 30, 2006 - Dec 19, 2011				
Unhedged CPO portfolio	0.000781	-	0.000509	-
Hedged CPO portfolio:				
Naïve hedge	0.001245	-59.3563	0.002317	-355.1356
OLS hedge	0.000781	0.095	0.000499	1.892
Intercept-BEKK-GARCH hedge	0.000737	5.682	0.0005	1.837
VAR-BEKK-GARCH hedge	0.000719	7.962	0.000489	3.882
Basis-BEKK-GARCH hedge	0.000681	12.789	0.000421	17.275
Intercept-CCC-GARCH hedge	0.000769	1.531	0.000543	-6.6563
VAR-CCC-GARCH hedge	0.000745	4.617	0.000458	10.075
Basis-CCC-GARCH hedge	0.000719	7.959	0.000539	-5.8768

Notes: 1. The variance of unhedged CPO portfolio is generated from the variance of CPO spot return. 2. The variance of hedged CPO portfolio is computed by equation (12). 3. The risk reduction is calculated by equation (13).

As observed in Table 6, it shows that naïve strategy is the worst strategy as it increases the risk of hedged portfolio. The VAR-BEKK-GARCH model is found as the superior model in Panel A as it reduces 50.88 per cent of the risk (in-sample) and 13.04 per cent of the risk (out-of-sample). In Panel B, besides having relatively high dynamic hedge ratios within the range of 0.48-0.56 (in-sample) and 0.33-0.40 (out-of-sample) as shown in Table 5, an assumption of CCC-GARCH model with the basis term offers the most effective risk reduction of 17.48 and 45.15 per cent for the in- and out-of-sample respectively. In Panel C, a basis-BEKK-GARCH model achieves the highest risk reduction of over 12-17 per cent for both in- and out-of-sample. Overall, it is clear that the hedging strategies with the basis term generally outperform in reducing the risk of CPO portfolio in Panel B and Panel C.

As compared between Panel B and Panel C, the marginal differences among models suggest that the CPO futures hedging strategies underperform across the Asian and global financial crises for both in- and out-of-sample respectively. As investors more concern about future performance, the out-of-sample shows risk reduction of the superior model declines sharply from 45.15 to 12.28 per cent. The low level of hedging effectiveness is observed when futures return exhibits high volatility and fat-tailed distribution over the period of 2006-2011. Overall, the result indicates that the linkage between spot and futures prices in the long run (basis) is important to fit the extreme volatility during the global financial crisis. In contrast, including a basis effect into the GARCH model cannot sustain its high performance in reducing the risk during the global financial crisis as compared to previous crisis.

5. Conclusions

This study extends Zainudin and Shaharudin (2011) on Malaysian crude palm oil (CPO) futures market by examining the hedging effectiveness based on the minimum-variance hedge ratios from eight model specifications. These models were evaluated during the three financial crises namely, the world economic recession in 1986, Asian financial crisis in 1997/1998 and global financial crisis in 2008/2009 respectively. Subsequently, in-and out-of sample of the minimum variance of hedge ratio is compared during each sub-period. As the in- and out-of-sample analysis provides same finding, this study focuses on the out-of-sample forecasting evaluation results.

Notable findings are: First, it is evidently clear that GARCH models with basis term outperform others during the Asian financial crisis (AFC) and global financial crisis (GFC) respectively. Second, during the Asian financial crisis, the high dynamic hedge ratios contribute to the superiority of CCC-GARCH model with risk reduction of 45.15 per cent. The declining hedge ratio in GFC leads to the emergence of BEKK-GARCH model which provides the most risk reduction of 17.26 per cent. Third, from AFC to GFC, the risk reduction of hedging strategy declines sharply from 45.15 to 17.28 per cent. Two possible reasons are; Firstly, unlike AFC, the epicenter of GFC was in the United States and subsequently extended to Europe. Secondly, episode of bad news was released to the market one after another in prolonged period, which caused ineffectiveness of hedging strategy as shocks were largely unanticipated.

Overall, this study concludes: First, the high dynamic hedge ratio during the Asian financial crisis implies that CPO market participants are sensitive to CPO spot and futures movement. Second, the superior GARCH model with the basis term cannot sustain its performance in terms of risk reduction during the crisis period. This shows that the Malaysian CPO futures market provides a low level of hedging effectiveness during the global financial crisis, which is mainly caused by excess kurtosis in the markets. This finding is found to be inconsistent with Ong *et al* (2012) who find that stable movement of CPO spot price in 2009-2010 contributes to the low level of hedging effectiveness.

The policy implication is clear. Although the effectiveness of Malaysian CPO futures is low during the recent crisis, the minimum-variance hedge ratio analysis has managed to compare the performance of various hedging models. By understanding the effectiveness of various hedging models, the CPO market participants can switch between the models in different volatility periods to cover their risk exposure in the spot market.

References

Ahmed S. (2007) Effectiveness of time-varying hedge ratio with constant conditional correlation: an empirical evidence from the US treasury market. *ICFAI Journal of Derivatives Markets* 4(2): 22-30.

Alizadeh, A.H., Kavussanos, M.G. and Menachof, D.A. (2004) Hedging against bunker price fluctuations using petroleum futures contracts: constant versus time-varying hedge ratios. *Applied Economics* 36 (12): 1337-1353.

Anderson, R.W. and Danthine, J.P. (1981) Cross hedging. *The Journal of Political Economy* 89(6): 1182-1196.

Baillie, R.T. and Myers, R.J. (1991) Bivariate GARCH estimation of the optimal commodity futures hedge. *Journal of Applied Econometrics* 6(2): 109-124.

Bollerslev, T. (1990) Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Review of Economics and Statistics* 72(3): 498-505.

Bollerslev, T., Engle, R.F. and Wooldridge, J.M. (1988) A capital asset pricing model with time-varying covariances. *Journal of Political Economy* 96(1): 116-131.

Brooks, C., Henry, O.T. and Persand, G. (2002) The effect of asymmetries on optimal hedge ratio. *The Journal of Business* 75(2): 333-352.

Central Bank Malaysia (2009) Monthly Statistical Bulletin July 2009. Kuala Lumpur: Central Bank.

Choudhry, T. (2002) Short-run deviations and optimal hedge ratio: evidence from stock futures. *Journal of Multinational Financial Management* 13(2): 171-192.

Choudhry, T. (2004) The hedging effectiveness of constant and time-varying hedge ratios using three Pacific Basin stock futures. *International Review of Economics and Finance* 13(4): 371-385.

Ederington, L.H. (1979) The hedging performance of the new futures market. *Journal of Finance* 34(1): 157-170.

Engle, R.F. and Kroner, K.F. (1995) Multivariate simultaneous generalized ARCH. *Econometric Theory* 11(1): 122-150.

Fama, E.F. (1984) Forward and spot exchange rates. *Journal of Monetary Economics* 14(3): 319–338.

Floros, C. and Vougas, D.V. (2004) Hedge ratios in Greek stock index futures market. *Applied Financial Economics* 14(15): 1125-1136.

Giannopoulos, K. (1995) Estimating the time varying components of international stock markets' risk. *The European Journal of Finance* 1(2): 129-164.

Howard, C.T. and D'Antonio, L.J. (1984) A risk-return measure of hedging effectiveness. *Journal of Financial and Quantitative Analysis* 19(1): 101-112.

Hill, J. and Schneeweis, T. (1981) A note on the hedging effectiveness of foreign currency futures. *Journal of Futures Markets* 1(4): 659-664.

Johnson, L.L. (1960) The theory of hedging and speculation in commodity futures. *The Review of Economic Studies* 27(3): 139-151.

Kroner, K.F. and Sultan, J. (1993) Time varying distribution and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis* 28(4): 535-551.

Kogan, L., Livdan, D. and Yaron, A. (2003) Futures prices in a production economy with investment constraints. Working Paper, MIT.

Lien, D., Tse, Y.K. and Tsui, A.K.C. (2002) Evaluating the hedging performance of the constant-correlation GARCH model. *Applied Financial Economics* 12(11): 791-798.

Lien, D. and Yang, L. (2008) Hedging with Chinese metal futures. *Global Finance Journal* 19(2): 123-138.

Malaysian Palm Oil Board. Available from http://www.mpob.gov.my/. Accessed 24 October 2012.

Moschini, G.C. and Myers, R.J. (2002) Testing for constant hedge ratios in commodity markets: a multivariate GARCH approach. *Journal of Empirical Finance* 9(5): 589-603.

Ng, V.K. and Pirrong, S.C. (1994) Fundamentals and volatility: storage, spreads, and the dynamics of metals prices. *Journal of Business* 67(2):203-230.

Ong, T.S., Tan, W.F. and Teh, B.H. (2012) Hedging effectiveness of crude palm oil futures market in Malaysia. *World Applied Sciences Journal* 19(4): 556-565.

Park, T.H. and Switzer, L.N. (1995) Time-varying distribution and the optimal hedge ratios for stock index futures. *Applied Financial Economics* 5(3): 131-137.

Stein, J.L. (1961) The simultaneous determination of spot and futures prices. *The American Economic Review* 51(5): 1012-1025.

Switzer, L.N. and El-Khoury, M. (2007) Extreme volatility, speculative efficiency, and the hedging effectiveness of the oil futures markets. *Journal of Futures Markets* 27(1): 61-84.

Tong, W.H.S. (1996) An examination of dynamic hedging. *Journal of International Money and Finance* 15(1): 19-35.

United Nations Development Program (UNDP)(2009) The Global Financial Crisis and the Malaysian Economy: Impact and Response. A Joint Report by the Institute of Strategic and International Studies (ISIS) and the Faculty of Economics and Administration (UNDP Malaysia).

Working, H. (1953) Futures trading and hedging. *The American Economic Review* 43(3): 314-343.

Wu, F., Guan, Z. and Myers, R.J. (2011) Volatility spillover effects and cross hedging in corn and crude oil futures. *Journal of Futures Markets* 31(11): 1052-1075.

Zainudin, R. and Shaharudin, R.S. (2011) Multi mean GARCH approach to evaluating hedging performance in the crude palm oil futures market. *Asian Academy of Management Journal of Accounting and Finance* 7(1): 111-130.