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An Empirical Evaluation of Hedging Effectiveness of Crude Palm Oil Futures Market in Malaysia

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Abstract: This paper evaluates the hedging effectiveness of the Malaysian crude palm oil futures market using daily settlement prices over the periods from January 4, 2010 to August 30, 2017. Hedge ratios and the hedging effectiveness are determined by employing four competing econometric models namely: the standard ordinary least square (OLS) regression model, vector error correction model (VECM) and two variations of the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models namely; diagonal-VECH and diagonal-BEKK GARCH models. The first two models estimate constant hedge ratios while the other two models estimate time varying hedge ratios. Hedging performance is evaluated and compared in terms of in-sample (Jan 2010 – Dec 2016) and out-of sample periods (Jan 2017 – Aug 2017) of the four hedge ratio models. The empirical results show that the MGARCH models particularly diagonal-BEKK GARCH model performs better than the other three models indicating that this model fits better in designing hedging strategy. The empirical finding suggests that the investors in crude palm oil markets in Malaysia can use CPO futures contract as an effective instrument to minimize the risk.

Keywords: Hedge ratio; Hedging effectiveness; Crude palm oil Malaysia; Vector error correction mechanism; OLS; MGARCH.

JEL Classification: G12; G13; G14; G15.

1. Introduction

Futures contract is defined as a legal agreement usually between two parties to buy or sell a particular commodity or financial instrument at a predetermined price at a specified time in future. These contracts are standardized to facilitate trading on a futures exchange and are settled daily. Some futures contracts particularly on financial assets (stock or equity indices) are settled in cash, while futures contracts particularly on commodities (e.g., palm oil, soybean etc.) are settled in physical delivery. Almost all exchanges throughout the world, futures contracts are available on different types of assets. Futures contract are used for different purposes depending on the goals of the trader (loss minimizing or gaining profit). However, futures contract has become the most common derivatives instruments of the investors for hedging the risk exposures that may arise from adverse price movements. The effectiveness of futures contracts in managing risks is critical to the development of futures market. To design a better strategy with futures contracts for hedging the risk exposures, it is important that the hedgers understand the optimal hedge ratio in order to be able to find the right number of futures contract for minimizing the risk.

Usually it is not possible to eliminate or offset the risk exposure completely. Instead, the investors attempt to neutralize the risk exposure by constructing the hedge in such a way so that it performs as close to perfect as possible. The most important and beneficial aspect of the use of a futures contract is that it removes the uncertainty of future price movements of the hedged item by locking in a price today. This also facilitates the hedging companies or corporations to eliminate the ambiguity relating to their expenses and profits in the futures. Since perfect hedge is almost impossible, it is important to choose a value for the hedge ratio defined as the ratio of the size of the position taken in futures contract to the size of the total exposure (Hull, 2015). Since the risk is most commonly measured as the volatility of portfolio returns, it is plausible to choose a hedge ratio that minimizes the variance of the portfolio returns known as the minimum variance hedge ratio or optimal hedge ratio. Optimal hedge ratio is determined as the ratio of the covariance between spot and futures return to the variance of futures return. Once hedge is in place, its effectiveness can be evaluated. A hedge is considered to be effective if the changes in the price of the hedging derivative instrument and the changes in the price of the hedged item roughly offset each other.

Like many other countries, Bursa Malaysia Derivatives (BMD) a subsidy of Bursa Malaysia Berhad also provides platform for the investors offering trade on three different categories of derivatives products such as the equity derivatives, financial derivatives and commodity derivatives. Derivatives market has been performing well with increased hedging activities to manage risks arising from volatile commodity prices and global currencies. As far as the futures contracts are concerned, the crude palm oil futures (symbolized as FCPO) denominated in Ringgit Malaysia (MYR), is the top performing futures contracts in the derivatives market of Bursa Malaysia. According to Bursa Malaysia Annual Report of 2016, as at 31/12/2016, the number of total contracts traded on the Bursa Malaysia Derivatives (BMD) exchange was 14.2 million in which CPO futures alone accounted for 11.4 million contracts. This was about 80.3% of the total futures contracts traded on BMD. In terms of open interest, CPO futures accounted for 83.7% of the total in the derivatives market at the same period.

FCPO has been in operation since October 1980 in the Kuala Lumpur Commodity Exchange (KLCE). Since then it has become the popular product as the top performing derivative contracts in Bursa Malaysia providing market participants (e.g., crude palm oil producers, refiners, millers, exporters and importers) with a global price benchmark for the crude palm oil market. KLCE in November 1998 merged with Malaysian Monetary Exchange and become the Commodity and Malaysian Monetary Exchange (COMMEX). Following the Asian financial crisis in 1997, Malaysian derivatives went through restructuring and emerged in 2003 as a Bursa Malaysia Derivatives' (BMD). Since then FCPO has been continuing its trading under the BMD. In 2009, CME (Chicago Mercantile Exchange) took a 25% stake in BMD and in 2010, all BMD products were listed and traded on the CME operated GLOBEX trading platform (The world's leading electronic trading platform) which allows individual and professional traders anywhere around the world to access all Bursa Malaysia Derivatives products including FCPO. Via FCPO, global fund managers, commodity trading advisers and proprietary traders can gain immediate exposure to the commodity market. CPO futures is traded today at a number of derivatives exchanges around the world but more popularly traded in BMD and CME. FCPO traded in BMD is available both in Ringgit Malaysia and USD-denominated contracts. It is a cash settle or physically deliverable contract. The crude palm oil futures traded at CME uses the CPO symbol and is available in USD denominated contracts. It is a cash-settled contract only and does not involve physical delivery of the underlying crude palm oil.

CPO futures contract is traded as a tool primarily by the market participants/players in the edible oils and fats industry (such as plantation companies, refineries, exporters and millers) to hedge and manage risk against the unfavorable movement of crude oil price in the physical market. Speculators use crude palm oil futures to gain from the price movement of the contract on the exchange. For each CPO futures, the contract size is equivalent to 25 metric tons of crude palm oil. The contract months are specified as the spot month and the next 5 succeeding months followed by alternate months up to 24 months ahead.

Palm oil in the agricultural sector is an important contributor to Malaysian foreign exchange earnings. Malaysia is currently the second largest palm oil producer in the world just next to its neighbor Indonesia. The major importers of Malaysian CPO are India, China, The Netherlands, Pakistan, Turkey, The USA, Vietnam and the Philippines. In 2015, palm oil exports contributed RM40.12 billion (5.2%) to Malaysian total exports of RM 777.36 billion. In 2016, palm oil exports contribution increased to RM41.44 billion (5.3%) in the total export earnings of RM785.93 billion. As of January to July 2017, palm oil contributed RM26.84 bill (5.1%) to the total export earnings of RM529.68 bill. This shows that palm oil revenue has economic significance for Malaysia. Like other agricultural commodities, palm oil price is also subject to wide margin of price fluctuation due to various factors including globalization, increased competition among the exporting countries, changes of climate leading to uncertainty in futures production or supply, changes in other competing edible oils, currency exchange rates, demand from importing countries, immigration policies and so on. The uncertainty of future palm oil price (higher/lower) has serious risk exposure for both the owners and the user of this product. Introduction and development of crude palm oil futures contracts is one of the efforts to minimize the risk exposure. To design a better hedging strategy with futures contracts to control the risk exposures, it is important that the hedger understand the optimal hedge ratio in order to be able to find the right number of futures contract (to buy/sell) for minimizing the risk. To what extent hedging strategy is effective largely depends on determining the appropriate or optimal hedge ratio. With regards to hedging approaches, they are basically three as highlighted in Sah and Pandey (2011) which are the traditional or naive hedge (1:1) ratio, Beta hedge ratio and the minimum variance hedge ratio. Among the three, the minimum variance hedge ratio strategy proposed by Johnson (1960) is used in the empirical studies of finance as the most plausible or appropriate measure to determine optimal hedge ratio.

There exist a large number of studies in the literature estimating optimal hedge ratios and the hedging effectiveness of futures contracts for equity, financial and commodity derivatives. In the literature, various distinct approaches have been employed to estimate optimal hedge ratio. Simple ordinary least square (OLS) regression approach was the most frequently adopted method to estimate optimal hedge ratio in the earlier studies which was introduced by Ederington (1979) and Anderson and Danthine (1980). The slope coefficient of the OLS regression in which changes in spot prices is regressed on changes in futures prices is known as the optimal hedge ratio. The other recently used methods are error correction mechanism (ECM), univariate and multivariate GARCHs. Hedge ratios estimated by OLS and ECM methods are time invariant or static, while hedge ratios estimated by GARCHs are time variant or dynamic.

A lot of previous studies such as Johnson (1960); Stein (1961); Ederington (1979); Floros and Vougas (2004); Dimitris *et al.* (2008) to name a few have also given theoretical description of hedging strategies. Johnson (1960) was the first who introduced minimum variance hedge ratio (MVHR) or optimum hedge ratio (OHR) which is the ratio of covariance between spot and futures return to the variance of futures return. This measure of hedge ratio is widely used in determining the hedging effectiveness. The estimate of hedge ratio and its effectiveness for equity futures (stock index futures) has been extensively investigated for different index futures contracts using different models across the countries. Some of the frequently cited studies are: Myers (1991); (Floros and Vougas, 2004;2006); Ahmed (2007); Degiannakis and Floros (2010); Gupta and Singh (2009); Bhaduri and Durai (2008), Sah and Pandey (2011) and Ong *et al.* (2012). They used different models to estimate hedge ratios and their effectiveness largely for equity futures.

The results derived from various methods by various studies indicate no consistency in determining the models and the optimal hedge ratios. Many of the studies (e.g., Lee C. F. *et al.* (2009); Kumar *et al.* (2008); (Myers, 1991); Park and Switzer (1995); Moschini and Myers (2002); (Floros and Vougas, 2004;2006); Choudhry (2004); Bhaduri and Durai (2007); Lee H. T. and Jonathan (2007) and so on) concluded that the time-varying or dynamic hedging model produce higher hedge ratios than the static hedging model. A few studies (e.g., Awang *et al.* (2014); Butterworth and Phil (2001); Bhargava and Malhotra (2007); Lien (2005) etc.) found that static models performs better than the dynamic hedge models. A recent study of Hsu *et al.* (2008) discovered that the time-varying copula-based GARCH are more effective hedging models than the other models such as the OLS, CCC-GARCH and DCC-GARCH.

As far as futures contracts in Malaysian derivatives market are concerned, there are few empirical studies investigated the topic from different angles by employing various measures including the OLS, ECM and GARCHs models. Studies of Go and Lau (2014); Ong *et al.* (2012); Zainudin and Shaharudin (2011); Awang *et al.* (2014) and Ibrahim and Sundarasan (2010) are of the most relevant studies.

Go and Lau (2014) examined the hedging effectiveness of crude palm oil (CPO) futures market from January 1986 to December 2013 with eight hedging models including constant and time varying hedging models. They divided the whole periods into three sub periods: world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/2009. They found that means of hedge ratios changed significantly over the three sub-periods. On average, the high optimal hedge ratios are found during the Asian financial crisis. 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 are very comparable during the Asian financial crisis. The study concluded that the hedgers need to make adjustment in the hedging strategies in response to different movement in market volatility.

Ong *et al.* (2012) evaluated hedging effectiveness of crude palm oil futures in Malaysia by employing OLS method. They estimated hedge ratios for each month during 2009-2011. They found varied hedge ratios over months ranging from maximum 66.77% in February 2009 to a minimum of 35.713% in June 2010. In terms of hedging effectiveness, the values were found ranging from 19% to 53%. They pointed out that this low level of hedging performance was due to stable crude palm oil spot price relative to crude palm futures price.

Awang *et al.* (2014) employed various hedge ratio estimation methods such as the conventional OLS, VECM, EGARCH and bivariate GARCH to investigate the hedging effectiveness of stock index futures markets in Malaysia and Singapore using daily settlement data from January 2000 to December 2010. Their study reported that the OLS model performed most effectively in both index futures markets, followed by EGARCH. Based on the findings, they concluded that OLS model serves as a better hedging model than other static and time-varying models in a direct hedge using stock index futures. The literature review above shows that there is no unique technique or model that can be considered as the best or superior model to estimate hedge ratios.

The present study applied four competing hedging models namely; the traditional OLS model, VECM model, the diag-VECH GARCH model and the diag-BEKK GARCH model to estimate hedge ratios and the hedging effectiveness for Malaysian crude palm oil futures markets. The study is structured as follows: In section 2, data descriptions are given while section 3 provides an overview of models adopted for computing the hedge ratios. Section 4 presents and analyses the empirical results followed by conclusions in section 5.

2. Data Description

In this study, the daily settlement prices data are used which are obtained from Bursa Malaysia Derivative (BMD) Berhad for the period from January 4, 2010 to August 29, 2017. This constitutes 1880 observations of trading days. The whole sample data is divided in to two: in-sample and out-of-sample. In sample data comprises of 1718 trading day observations (Jan 2010 – Dec 2016), and the out-of-sample is 162 trading day observations (Jan 2017 – Aug 2017). Unlike other studies that used Malaysia Palm Oil Board (MPOB) provided data representing for CPO spot price which are collected from various regional markets, this study used crude palm oil spot futures prices of bursa Malaysia derivatives exchange as a proxy for spot crude palm oil price and the CPO settlement price for the next two month contract as the CPO futures price. CPO price for the next two month contract is the most active futures contract. CPO spot prices obtained from MPOB may not represent CPO spot prices appropriately due to various reasons such as the market imperfections and the differences in the quality of the underlying commodity (CPO) and hence the hedging information may be misled.

The choice of selecting CPO futures spot price as a proxy for CPO spot price is based on the previous studies (Kumar *et al.*, 2008). Furthermore, the CPO spot price data provided by MPOB were not matching with the futures contract data provided by Bursa Malaysia Derivatives Berhad. A total of 23 days of observations were missing from the MPOB provided CPO spot price due to either ‘no trade’ or ‘public holiday’ whereas in the case of FCPO futures prices, a total of 1880 trading days were found excluding the public holidays. The data are transformed into natural logarithmic form and then expressed into logarithmic return. Figure 2.1 shows the pattern of spot and futures prices expressed in natural log while figure 2.2 shows the behavior of logarithmic returns of the prices. The return series in figure 2.2 indicates the pattern of volatility clustering.

Figure-2.1. Pattern of spot and futures prices of CPO in natural log

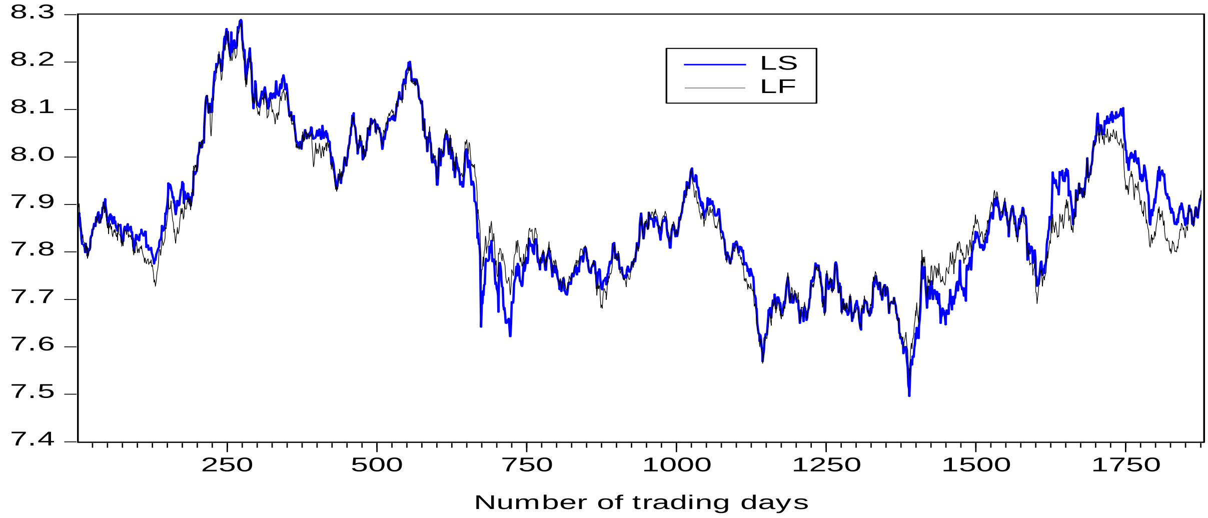
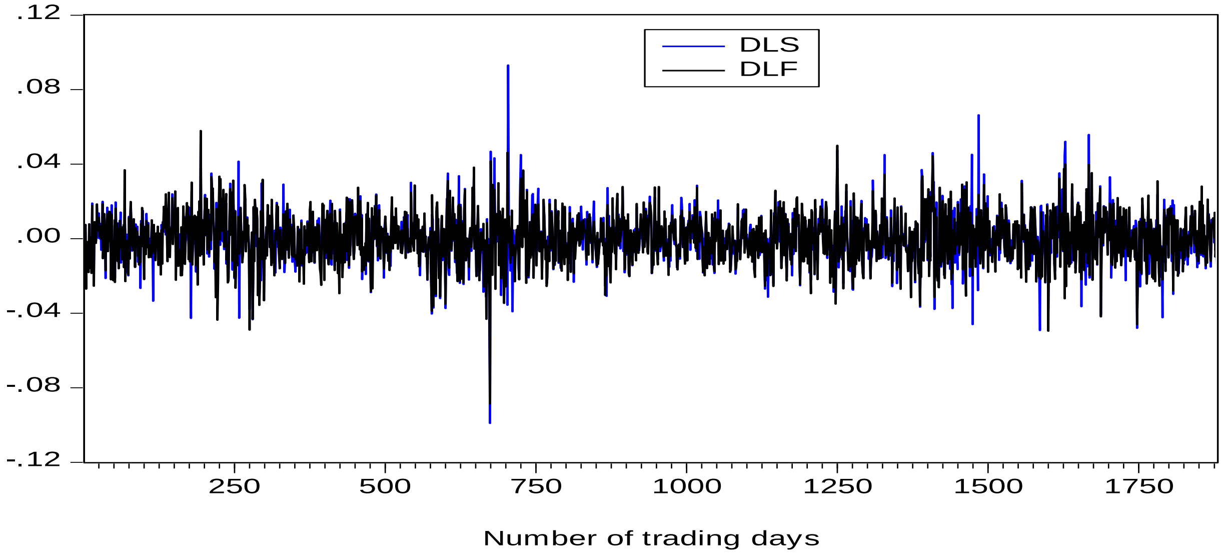


Figure-2.2. Pattern of spot and futures prices of CPO in logarithmic returns



2.1. Data Stationarity Test (Unit root test)

The standard unit root test is conducted by means of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The test establishes that both spot and futures series at the levels are non-stationary, while their first differences (returns) are stationary. The results are presented in table 2.1 below:

Table-2.1. Unit root test for stationarity

Variables (level)	ADF Statistics	PP Statistics	Variable (First Difference)	ADF Statistics	PP Statistics
LS	-1.6541	-1.7792	ΔLS	-38.4216*	-38.4478*
LF	-1.6725	-1.7917	ΔLF	-39.2702*	-39.3281*

*denote significance at 1% level.

2.2. Cointegration Test

To ascertain whether there exists any cointegrating relationship between the two price series, Johansen (1991) test procedure is applied in which there are two statistics: the *trace statistics* and the *maximum eigenvalue statistic*. Both statistics in the Johansen's test suggest that spot and futures prices are cointegrated, with one cointegration relationship. Furthermore the cointegrating vector normalized on *LS* exhibits that the long run cointegrating coefficient with respect to *LF* is statistically significant. The test results are presented in table 2.2 below:

Table-2.2. Johansen cointegration test (Spot vs. Futures).

Hypothesis	Eigenvalue	λ_{TRACE}	95% C.V.	λ_{MAX}	95% C.V.
None*	0.019290	35.93068	15.49471	33.44465	14.26460
At most 1	0.001447	2.486024	3.841466	2.486024	3.841466

Note: Both *Trace* and *Max-eigenvalue* tests indicate 1 cointegrating eqn. at the 5% level.
*denotes rejection of the hypothesis at the 5% level.

The corresponding unrestricted cointegrating vector normalized on *LS* is-

LS	LF
1.000000	-1.060218 (0.03256)

Standard error in parentheses

3. Methodology for Computing Optimal Hedge Ratio

There are a number of different econometric methods are available/proposed in the literature to compute the optimal hedge ratios. In this paper, we have employed four different competing models to estimate hedge ratios. The models are presented as bellow:

3.1. Ordinary Least Square (OLS) Model:

This method is a simple linear regression method which involves regression of change in spot price against the change in future price as-

$$\Delta S_t = \alpha + \beta \Delta F_t + u_t, \qquad u_t \sim N(0,\ \sigma^2) \tag{1}$$

Where $\Delta S_t = logS_t - logS_{t-1,}\ and\ \ \Delta F_t = logF_t - logF_{t-1}$. u_t is the error term. Δ is the first difference operator. The coefficient β is the optimal hedge ratio which can also be calculated as $h^* = \rho\frac{\sigma_S}{\sigma_F} = \frac{Cov(\Delta S, \Delta F)}{\sigma^2{}_F}$, where σ_S and σ_F are the standard deviations of ΔS and ΔF respectively. ρ is the coefficient of correlation between the two. The OLS estimate hedge ratio (slope of the regression) is considered reasonable if the underlying assumptions u_t has zero mean, same variance, and are uncorrelated are fulfilled. But in reality there are substantial evidences in the financial literature suggesting that as far as returns to financial series are concerned these assumptions are not compatible. This method also fails to take into account the time varying nature of hedge ratios.

3.2. Cointegration and Error Correction Mechanism (ECM) Approach: *Vector Error Correction Model (VECM)*

Error correction model is applied when the underlying series are cointegrated. Sometimes two or more time series have the common stochastic trend. With such trends they can move together so closely over the long run which can refer to as the long run equilibrium relationship between the series. In the short run, however there may be disequilibrium which is treated as the error term. This error term can be used to correct the short run disequilibrium. According to Engle and Granger (1987) who popularized this error correction term stated that if two series are cointegrated, then the relationship between them can be expressed by ECM. The time series that appear to share a common stochastic trend are said to be cointegrated. Financial time series often exhibit such a common stochastic trend. Cointegration and ECM approach can be implemented by applying different test methods. In this study we employed Johansen (1991) test method to test the cointegration. If the level series of spot and the futures price are non-stationary and integrated of order one $I(1)$, then the VECM can be applied to estimate hedge ratio. The VECM specification is expressed as follows:

$$\begin{aligned}
\Delta S_t &= \alpha_S + \sum_{i=1}^{k} \beta_{Si} \Delta S_{t-1} + \sum_{i=1}^{k} \delta_{Fj} \Delta F_{t-i} + \lambda_S Z_{t-1} + \mu_{St} \\
\Delta F_t &= \alpha_F + \sum_{i=1}^{k} \beta_{Fi} \Delta F_{t-1} + \sum_{i=1}^{k} \delta_{Si} \Delta S_{t-i} + \lambda_F Z_{t-1} + \mu_{Ft}
\end{aligned} \tag{2}$$

Where, $Z_{t-1} = S_{t-1} - \phi F_{t-1}$ is called the error correction term, ϕ is the cointegrating coefficient, λ_S and λ_F are adjustment parameters. Optimal hedge is estimated as the ratio of covariance of residuals of spot and futures return and variance of residual of futures retrieved from VECM as-

$$h^* = \frac{\sigma_{SF}}{\sigma_F^{\ 2}} \tag{3}$$

Where,

$$\text{covariance } (\mu_{st}, \mu_{ft}) = \sigma_{SF}$$

$$\text{variance } (\mu_{ft}) = \sigma_F^{\ 2}$$

$$\text{variance}(\mu_{st}) = \sigma_S^{\ 2}$$

3.3. The Multivariate GARCH (*p*, *q*) Model

GARCH model is the generalization of the ARCH model initially introduced by Bollerslev (1986). It is capable of capturing volatility clustering effect which can be found in most of the financial and macroeconomic return time series. A return time series with some periods of high volatility and some periods of low volatility is said to exhibit volatility clustering. In the face of such structure of return time series or the ARCH-effect that the return data series possesses, the estimation of hedge ratio and the hedging effectiveness may not be appropriate. GARCH model can take care of ARCH effects in the residuals.

Multivariate GARCH model is the generalization of univariate GARCH of Bollerslev (1986). The most straightforward generalized multivariate GARCH is the *vech* GARCH proposed by Bollerslev and Wooldridge (1988). The *vech* GARCH model has been further generalized and applied in financial econometrics. The simplest and possible lowest dimensional multivariate GARCH model is a bivariate GARCH (BGARCH). Some of the popular and successfully applied versions of the bivariate GARCH models are the diagonal-*vech* GARCH (Diag-VECH GARCH), the diagonal-BEKK GARCH (Diag-BEKK GARCH), Constant Conditional Correlation GARCH (CCC-GARCH) and Dynamic Conditional Correlation GARCH (DCC-GARCH) models. The univariate GARCH of Bollerslev (1986) and the multivariate GARCH are very similar in spirit except that in addition to variance equations, the multivariate GARCH also specifies the covariance equations. This study employed two versions of MGARCH namely: the *diag*-VECH GARCH and the *diag*-BEKK GARCH models.

3.3.1. The *diag*-VECH GARCH (1, 1) Model

The diagonal *VECH* GARCH is the restricted version of the general *VECH* model. The common specification of the general *VECH* GARCH model (initially due to Bollerslev and Wooldridge (1988)) for a lowest-dimensional system of two-assets (N = 2) is written as-

$$vech(H_t) = C + A vech(\xi_{t-1}\xi_{t-i}{}^{'}) + B\ vech(H_{t-1}), \quad \xi | I_{t-1} \sim N(0, H_t)$$

Where H_t is a 2 x 2 conditional variance-covariance matrix, ξ_t is a 2 x 1 error vector, $I_{t\text{-}1}$ is the information set at time *t-1*, C is a 3 x 1 parameter vector, A and B are 3 x 3 parameter matrices. The elements in the *vech* model *vech* (H_t) = h_t are written out as-

$$h_t = \begin{bmatrix} h_{11,t} \\ h_{22,t} \\ h_{12,t} \end{bmatrix} = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{31} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} u_1^{\ 2} \\ u_2^{\ 2} \\ u_1 u_2 \end{bmatrix}_{t-1} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{22} \\ h_{12} \end{bmatrix}_{t-1}$$

Where $h_{ii,t}$ represent the conditional variances at time period t of the two-asset return series (i = 1, 2), and $h_{ij,t}$ ($i \neq j$) represent the conditional covariances between the asset returns. The general *vech* model is an unrestricted model. The representation of the general *vech* model although very general and flexible, it has two disadvantages. Firstly, it has serious computational difficulties as the number of assets in the model increases. For example, in the case of the lowest-dimensional system (with N = 2) and p = q = 1, the *vech* model requires to estimate 21 parameters and the number of parameters to be estimated increased sharply along with the increase of the number of assets in the model. For N = 3 and p =q = 1, the number of parameters to be estimated is 78 and so on. Second disadvantage is that only a sufficient condition for the positive definiteness of the matrix H_t is known.

To reduce these disadvantages of the general *vech* model, Bollerslev and Wooldridge (1988) proposed a restriction on the conditional variance-covariance matrix to the form in which the coefficient matrices A and B are assumed to be diagonal. In this case the number of parameters to be estimated is reduced to 9 from 21 for two assets case. Furthermore, the necessary and sufficient conditions for the definiteness of H_t are also obtained. This restricted version of the *vech* model is known as the diagonal *vech* model. In a simple bivariate (For N = 2 and p = q = 1) diagonal *vech* GARCH model, there are three conditional equations, one for each conditional variance and one for the conditional covariance. The conditional variances and the covariance equations of the diagonal VECH GARCH are presented as follows:

$$h_t = \begin{bmatrix} h_{11,t} \\ h_{21,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} u_1{}^2 \\ u_1 u_2 \\ u_2{}^2 \end{bmatrix}_{t-1} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{21} \\ h_{22} \end{bmatrix}_{t-1}$$

Or

$$h_{11,t} = c_1 + a_{11} u_1{}^2{}_{t-1} + b_{11,t} h_{11,t-1}$$

$$h_{21,t} = c_2 + a_{22} u_{1t-1} u_{2t-1} + b_{22,t} h_{21,t-1} \qquad (4)$$

$$h_{22,t} = c_3 + a_{33} u_2{}^2{}_{t-1} + b_{33,t} h_{22,t-1}$$

Where, $h_{11,t}$ and $h_{22,t}$ are the conditional variances of the errors $u_{1,t}$ and $u_{2,t}$ and $h_{12,t}$ is the covariance between the errors u_{1t} and u_{2t}. The time varying hedge ratio for each time period t is calculated as follows:

$$h_t = \frac{h_{12,t}}{h_{22,t}} \qquad (5)$$

3.3.2. The *diag*-BEKK GARCH (1, 1) Model

Baba *et al.* (1990) proposed a parameterization of the general *vech* GARCH equations that ensures the positive definiteness of the covariance matrix H_t and also allows to estimate low-dimensional multivariate GARCH systems with less computational difficulties. The BEKK parameterization for a symmetric GARCH is written as-

$$H_t = CC' + A'\xi_{t-1}\xi_{t-1}{}'A + B'H_{t-1}B$$

Where, A and B are 2 x 2 matrices of parameters (for a 2-asset case) and C is triangular. To make the model parsimonious in estimating the numbers of parameters, BEKK model assumes that the coefficient matrices A and B are diagonal. The number of parameters to be estimated (with $p = q = 1$, $N = 2$) in this model is reduced to 7. H_t is the conditional variance-covariance matrix at time t, ξ_t is the disturbance vector. The *diag*-BEKK GARCH (1, 1) with N=2, $A = diag(a_{11,} a_{22})$, and $B = diag(b_{11,} b_{22})$ is expressed as-

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22},t \end{bmatrix} = CC' + \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_1{}^2 & \varepsilon_1, \varepsilon_2 \\ \varepsilon_2, \varepsilon_1 & \varepsilon_2{}^2 \end{bmatrix}_{t-1} \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}$$

or

$$h_{11,t} = c^2{}_{11} + a^2{}_{11,} \varepsilon_1{}^2{}_{t-1} + b^2{}_{11} h_{11,t-1}$$

$$h_{22,t} = c^2{}_{22} + a^2{}_{22} \varepsilon_2{}^2{}_{,t-1} + b^2{}_{22} h_{22,t-1} \qquad (6)$$

$$h_{12,t} = a_{11,} a_{22,} \varepsilon_{1,t-1,} \varepsilon_{2,t-1} + b_{11,} b_{22,} h_{12,t-1}$$

Where $h_{11,t}$ and $h_{22,t}$ are the conditional variances of the errors $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ respectively and $h_{21,t}$ is the covariance between the errors $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. In the *BEKK* parameterization, there are also three conditional equations, one for each conditional variance and one for the conditional covariance. Each equation is a GARCH (1, 1). *BEKK* model does not impose cross equation restrictions and is parsimonious in estimating the number of parameters for a low dimensional case. The time varying hedge ratio for each time period t is calculated in the same way as the *diag*-VECH-GARCH as follows:

$$h_t = \frac{h_{12,t}}{h_{22,t}} \qquad (7)$$

3.3.3. Measure of Hedging Effectiveness

The hedging effectiveness is defined as the proportion of the variance that is eliminated by hedging (Hull, 2015). In other words, the effectiveness of the minimum variance hedge can be determined by examining the percentage reduction in the variance of the return of the hedged portfolio using the measure (Ederington, 1979) as-

$$\text{Hedge effectiveness } (HE) = \frac{Var(u) - Var(h)}{Var(u)} \text{ X } 100 \qquad (8)$$

Where,

$$Var(u) = \sigma^2 S$$
$$Var(h) = \sigma^2 S + h^2\sigma^2 F - 2h\sigma_{SF} \qquad (9)$$

Var(u) and *Var(h)* are the variances of unhedged and hedged positions respectively, h is the minimum variance hedge ratio and σ_{SF} is the covariance between the spot and futures price change. Hedging effectiveness of the four hedging models are evaluated by using this measure for full sample, in-sample and out-of-sample data.

4. Empirical Results

4.1. In-Sample Hedge Ratios and Hedging Effectiveness

In this section, the results particularly the optimal hedge ratios and the measure of their effectiveness for in-sample data computed from different models as described in section 3 are presented.

4.1.1. The OLS estimates

Table 4.1 below presents the results derived from OLS regression (eqn. 1). The slope coefficients β is 0.85551 which represents as the optimal hedge ratio. It is statistically highly significant and less than unity. The *R*-squared value is 0.7161 indicating a reasonably good fit model. *R*-squared value measures the hedging effectiveness of the OLS model. It means hedge ratio obtained from OLS regression provides approximately 72% reduction in the variance of the position.

Table-4.1. OLS estimate results

	Coefficient	Std. error	*t*-statistic	Prob.	R^2
α	0.0000438	0.00017746	0.246577	0.8053	0.7160521
β	0.8555145	0.01308951	65.76352	0.0000	

The OLS model however did not pass residual diagnostic test for 'no serial correlation' and 'Heteroscedasticity'. In other words, the model exhibits the presence of serial correlation and Heteroscedasticity in the residuals.

4.1.2. VECM Estimates

Since the spot and futures prices are cointegrated, VECM is used to estimate hedge ratio using equation 3. The calculated hedge ratio is 0.85927. The corresponding hedging effectiveness (*HE*) is 73.03% computed by using equation 8. Both are higher than the optimal hedge ratio and the hedging effectiveness estimated from OLS indicating that VECM performs better than the OLS model.

Table-4.2. Optimal hedge ratio and its effectiveness derived from VECM

	Values
Covariance (μ_s, μ_f) = σ_{SF}	0.0001592403
Variance (μ_f) = σ^2_f	0.0001853199
Variance (μ_s) = σ^2_s	0.0001873584
Hedge ratio (*h) = σ_{SF}/σ^2_f**	**0.859272569**
Var (*h*) = variance of the hedged position	0.0000505276
Var (*u*) = variance of the unhedged position	0.0001901699
Hedging effectiveness (HE)	**0.73031563**

4.1.3. Bivariate GARCH (1, 1) Estimates

Table 4.3 presents the estimated hedge ratios and their effectiveness derived from the BGARCH models (4 & 6). The estimated parameters of the BGARCH models are all both plausible and statistically significant (in order to save space parameter estimates results are not presented here but available on request). The average or mean hedge ratios estimated from BGARCH models are higher than both the OLS and VECM estimate hedge ratios. The diag-BEKK GARCH provides higher values than the diag-VECH GARCH. It is to be noted here that the BGARCH computes dynamic hedge ratios which are more realistic than the constant hedge ratios computed by the OLS and the VECM models. Mean hedge ratios and the hedging effectiveness obtained from bivariate GARCH (Diag-VECH and Diag-BEKK) models are as follows:

Table-4.3. The BGARCH (1, 1) estimates

	Diag-VECH GARCH (1, 1)	**Diag-BEKK GARCH (1, 1)**
Mean (*h)**	**0.859309745**	**0.861363116**
Minimum (*h**)	0.129354678	0.135981459
Maximum (*h**)	1.202116456	1.180344000
Var(*u*) = unhedged position	0.000190170	0.000190170
Var(*h*) = hedged position	0.000049268	0.000049226
Hedge effectiveness (*HE*)	**0.758370958**	**0.761008217**

From the table 4.3 above, it can be seen that both in terms of hedge ratios and the hedging effectiveness, diag-BEKK GARCH model performs better than the diag-VECH GARCH model. The average/mean hedge values estimated from diag-VECH and diag-BEKK GARCH models are 0.85931 and 0.86136 respectively. The corresponding hedge effectiveness measures are 75.84% and 76.10% respectively. However, there is a wide variation in the hedge ratios across the periods for both models suggesting that the hedgers need to rebalance their hedge positions in futures contracts time to time in order to remain protected from risk exposure.

Figure 4.3 & 4.4 exhibit time varying hedge ratios derived from the BGARCH (1, 1) models. The optimal hedge ratio series obtained from the BGARCH models appear to be stationary when a unit root test is conducted by ADF test. In both cases, the null hypothesis (hedge ratio contains unit root) was strongly rejected by the data (ADF test statistics: -11.0082 for diag-VECH and -12.78207 for diag-BEKK) at 1% critical value which is -3.433957. These show that hedge ratios are stable.

Figure-4.3. & 4.4. Time-varying hedge ratios estimated from BGARCH (1, 1) models.

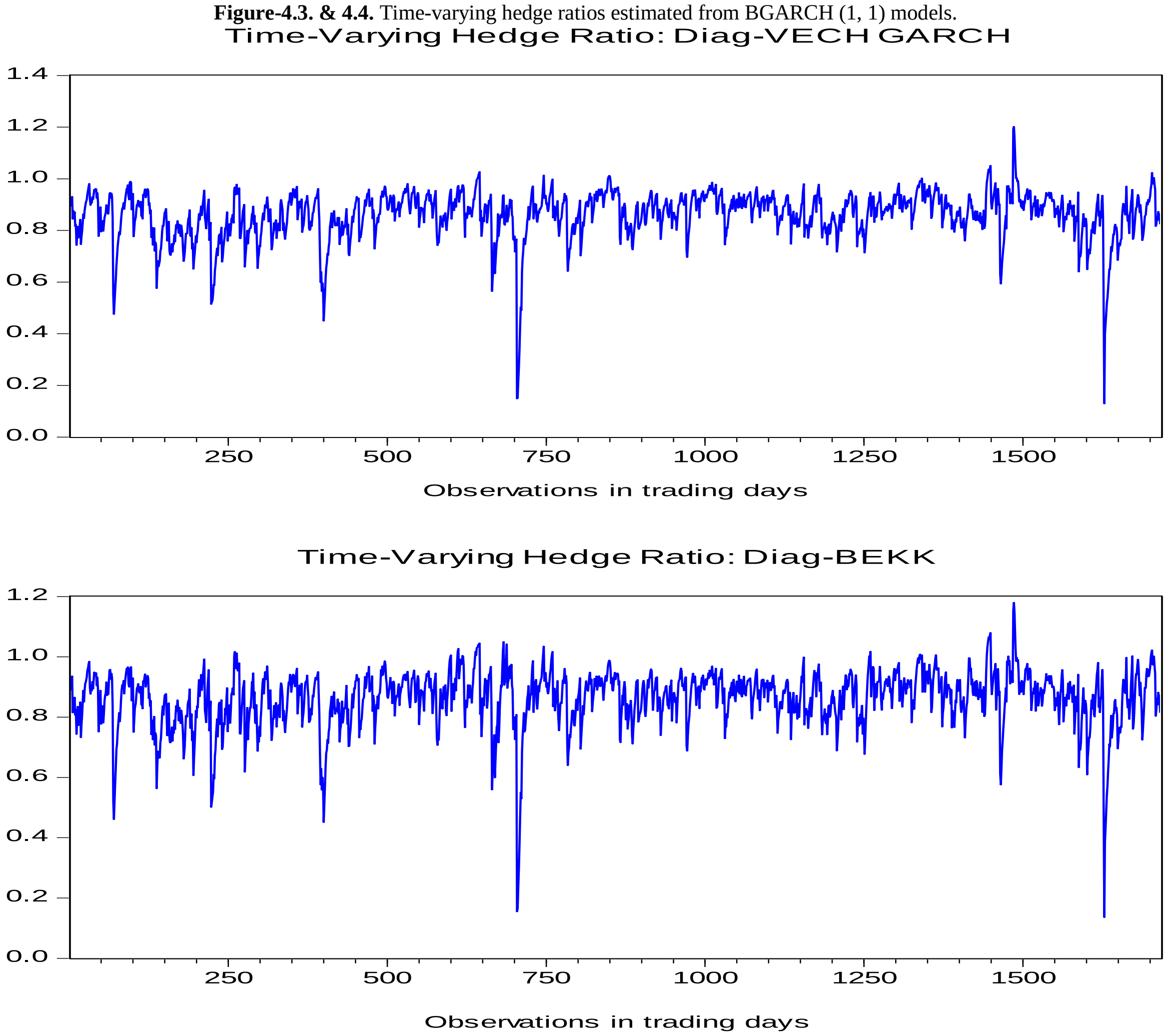


Table 4.4 below presents the estimated optimal hedge ratios and their effectiveness derived from different models to compare their relative performance within sample. The comparison shows that the optimal hedge ratios estimated by BGARCH (1, 1) models are higher than the constant hedge ratio models and also provide greater variance reduction. Between the BGARCH (1, 1) models, however, diag-BEKK GARCH appears to be better both in terms of hedge ratios and in reducing variance. Low hedge ratio underestimates the number of futures contract a trader should long or short to hedge the spot price exposure.

Table 4.4. Summary of optimal hedge ratios and the hedging effectiveness (HE) estimated by different models

Models	**Optimal hedge ratio (*h**)**	**Variances of returns, $\sigma^2_{H,t}$**	**Variance reduction (HE)**
Un-hedged	0	0.000190170	-
OLS	0.85551	0.000053998	71.61%
VECM	0.85927	0.000050528	73.03%
BGARCH (Diag-VECH)	0.85931	0.000049268	75.84%
BGARCH (Diag-BEKK)	0.86136	0.000049226	76.10%

The results in estimating hedge ratios by using spot futures price as a proxy for spot palm oil price show significant improvement over the past studies (e.g., Go and Lau (2014); Ong *et al.* (2012); (Awang *et al.*, 2014) etc.) on FCPO conducted in Malaysia signifying that the crude palm oil futures market in Malaysia provides a reasonably higher level of hedging efficiency.

5. Out-of-the Sample Hedging Performance

Hedging effectiveness is also evaluated for out-of-sample periods which is said to be more reliable measure to evaluate effectiveness of the hedge ratios. This is due to the fact of the concern of the investors about the futures performance. For out-of-sample test, 162 trading days observations of the sample (January 3, 2017 to August 30, 2017) are used. Hedge ratios estimated for the periods (January 4, 2010 to December 30, 2016) are used to evaluate the out-of-the sample or post sample hedging performance. The results of the out-of-sample (post-sample) periods performance are reported in table 5.1.

Table-5.1. Out-of-sample comparisons of hedging effectiveness of different models

Models	Variances of portfolio returns, $\sigma^2_{H,t}$	Variance reduction
Un-hedged	0.0001414371	-
OLS	0.0000366378	74.10%
VECM	0.0000355538	73.83%
BGARCH (Diag-VECH)	0.0000359869	74.35%
BGARCH (Diag-BEKK)	0.0000366412	74.58%

The out-of sample test results presented in table 5.1 clearly show that the time varying hedge ratios estimated by BGARCH (1, 1) models perform better than the constant hedge ratios estimated by OLS and the VECM in reducing the risk. Both in sample and post sample data produce consistent results that the dynamic hedging models are preferable in hedging performance than the constant hedging models. These results are consistent with many other papers such as: Park and Switzer (1995); Yang and Allen (2004); Choudhry (2004); Floros and Vougas (2006); Bhaduri and Durai (2008); Kumar *et al.* (2008). However, the preference of dynamic hedging models over the constant hedge models are to some extent depends on investors risk preferences (Myers, 1991) and the trade-off between the cost (transactions) and the benefit in risk reduction (Park and Switzer, 1995). Use of GARCH method requires the investors to adjust their position time to time which involves transaction costs. If the investors are extremely risk-averse and the rebalancing of the position is not too frequent, then the use of GARCH models may be the preferable strategy to hedge the risk.

6. Conclusion

This study evaluates hedging effectiveness of crude palm oil futures contracts traded on Bursa Derivatives Malaysia (BMD) berhad. Three different competing econometric models (OLS, VECM and Bivariate GARCH models) are employed to estimate the hedge ratios and their effectiveness. Hedging effectiveness of different models is evaluated for in sample periods (January 4, 2010 to December 30, 2016) that consist of 1718 trading day observations and the out-of-sample periods (January 3, 2017 to August 30, 2017) that consist of 162 trading day observations. The study found that bivariate GARCH (1, 1) models perform better both in terms of producing larger hedge ratios and reducing of larger proportion of the risk than the other hedge models employed in this study. The results are consistent for both in sample and the out-of-sample periods. The empirical findings suggest that bivariate GARCH (particularly diag-BEKK GARCH) model can be used as a better model to construct hedging strategy in Malaysian crude palm oil futures market. Furthermore the GARCH model is also better known as able of capture the conditional variances between the change in spot price and the futures prices. Overall from the results it can be concluded that the CPO futures contract in Malaysia is reasonably a good derivative instrument to hedge the risk associated in the spot price fluctuation of the crude palm oil. In other words, it provides reasonably a good level of hedging effectiveness and the bivariate GARCH can be utilized as a potentially superior to the constant hedge models to construct hedging strategy. Further research may be conducted by using different futures (e.g., futures 1, futures 2 and so on) contracts to compare their relative effectiveness and also based on data frequency (e.g., weekly or monthly data).

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