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Optimal hedge ratio and the hedging performance of commodity futures: The case of Malaysian crude palm oil futures market

Mohd Aminul Islam
Department of Computational and Theoretical Sciences
Faculty of Science,
International Islamic University Malaysia
Bandar Indera Mahkota,
25200 Kuantan, Pahang

ABSTRACT

This paper aims to examine the hedging performance of the crude palm Oil futures Market in Malaysia. The optimal hedge ratios and the hedging performance are examined for two different futures contracts denoted as futures 1 and futures 2 using daily settlement prices from January 4, 2010 to October 31, 2017. Four econometric models comprising of the standard ordinary least square (OLS), vector auto-regression (VAR), vector error correction model (VECM) and the bivariate generalized autoregressive conditional heteroscedasticity (BGARCH) models are employed to compute hedge ratios. The first three models estimate constant hedge ratios while the last model estimates time varying hedge ratio. The effectiveness of the hedge ratios for two contracts is evaluated in terms of in-sample and out-of-sample performance. For in-sample performance, January 4, 2010 to October 31, 2016 period is used while for out-of-sample validation, a one year data from November 2016 to October 31, 2017 is used. The empirical results show that the bivariate GARCH model performs better in the reduction of risk for both periods and the nearest futures contract (next one month contract) appears to be better in hedging than the far futures contract (next two month contracts). This suggests that the investors can use crude palm oil futures contract particularly the nearest futures contract as an effective instrument to hedge the risk and the bivariate BEKK-GARCH as an efficient model for designing hedging strategy.

Keywords: Hedging, crude palm oil futures, Malaysia, vector error correction model, bivariate diag-BEKK GARCH

1. Introduction

Futures contracts are one of the most common derivatives instruments used by the investors to hedge 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 hedger understand the optimal hedge ratio in order to be able to find the right number of futures contract for minimizing the risk 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. All most all exchanges throughout the world, futures contracts are available on different types of assets. 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 companies or corporations to eliminate the ambiguity relating to their expenses and profits in the futures. It is very unlikely to eliminate or offset the risk exposure completely as the price changes of the spot and futures are often not in proportion. The investors thus attempt to neutralize the risk exposure by constructing the hedge strategy in such a way so that it performs as close to perfect as possible. Hedging strategy thus depends much on the optimal hedge ratio which is defined as the ratio of the size of the futures position to the size of the spot position.

In the hedging literature, researchers have distinguished two main hedging strategies namely-the traditional or naïve hedge and the minimum variance hedge. The traditional or naïve hedging strategy assumes that the appropriate/optimal hedge ratio for any spot position equals 1.0. In other words, for each unit or value of spot position held an equal and opposite number of hedge instrument (futures) should be employed. According to the assumption of this strategy, if the spot and futures price changes are perfectly correlated, taking a futures position exactly equal to the spot position in magnitude with an opposite sign is enough to completely eliminate the price risk. However, in real world such a perfect matches in correlation between the changes of the spot price and the futures price are rarely found. Therefore, where the goal of hedging is to minimize the variance of the portfolio return, traditional or naïve hedging is unlikely to provide the optimal hedge results. Since the perfect hedge (1 to 1) is almost impossible, an investor needs to choose a value for the hedge ratio which is appropriate or optimal. A widely used value for the hedge ratio is the one that minimizes the variance of the value of the hedged position. This is referred to as the minimum variance hedge ratio (MVHR) proposed by Johnson (1960) and Stein (1961) and developed further by Ederington (1979). The MVHR is the ratio of covariance of the spot and futures price changes to the variance of the futures price changes.

Bursa Malaysia Derivatives (BMD) a subsidy of Bursa Malaysia Berhad 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 most active and 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 FCPO 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 FCPO 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). FCPO has been continuing its trading since then 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. Via FCPO, global fund managers, commodity trading advisers and proprietary traders can gain immediate exposure to the commodity market in Malaysia. Today CPO futures is traded at a number of derivatives exchanges around the world but more popularly traded in BMD and CME. Crude Palm Oil futures traded in BMD is available in both 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 later one is a cash-settled contract only and does not involve physical delivery of the underlying crude palm oil. Hedgers use crude palm oil futures contract to manage risk against the unfavourable movement of crude oil price in the physical market while speculators use crude palm oil futures to gain from the price movement of the contract on the exchange. For each crude palm oil futures, the contract size is equivalent to 25 metric tons. The futures 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. This shows that palm oil revenue has economic significance for Malaysia. Like other agricultural commodities, palm oil price is also subject to price fluctuations. 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 for minimizing the risk. To what extent hedging strategy is effective largely depends on determining the appropriate or optimal hedge ratio.

A large number of previous studies have estimated optimal hedge ratios and the hedging effectiveness of futures contracts for equity, financial and commodity derivatives. Various distinct approaches have been used to compute 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 and r-squared is as the measure of hedging effectiveness. The other recently used methods are vector autoregression, error correction method (residual based single equation approach or VAR-based approach), univariate GARCH and various forms of multivariate GARCH models. Hedge ratios estimated by OLS, ECMs are time invariant or static, while hedge ratios estimated by GARCHs are time variant or dynamic.

The estimate of optimal hedge ratio and its effectiveness for 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), Kroner and Sultan (1993), Ghosh (1993), Park and Switzer (1995), Kavussanos and Nomikos (2000), Chodhry (2004), Floros and Vougas (2004, 2006), Ahmad (2007), Bhaduri and Durai (2008), Gupta and Singh (2009), Degiannakis and Floros (2010), Sah and Pandey (2011), Ong, Tan, and Teh (2012) to name a few. They all used different models to estimate hedge ratios and their effectiveness for futures contracts on different assets. Few of the previous studies such as Working (1953), Johnson (1960), Stein (1961), Ederington (1979), Floros and Vougas (2004) have also given theoretical description of the hedging strategies.

The results from various methods employed by various studies indicate no consistency in determining the optimal hedge ratios as well as the performance of different contracts periods. Many of the studies such as Cheng-Few Lee 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 and Yoder (2007) 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 Holmes, 2001; Bhargava and Malhorta 2007; Lien 2005) 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 You-How Go and Wee-Yeap Lau (2014), Ong, et. al. (2012), Zainudin and Shaharudin (2011), Awang et. al. (2014), Ibrahim and Sundarasan (2010) are of the most relevant studies.

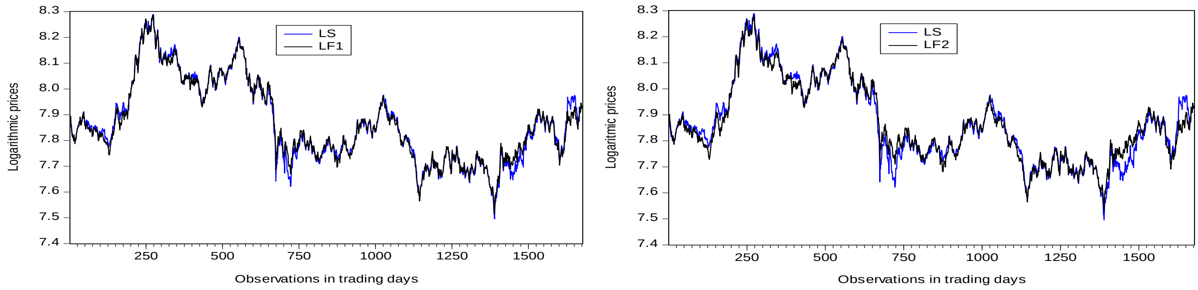
You-How Go and Wee-Yeap (2014) examined the hedging effectiveness change of Crude Palm Oil (CPO) futures market from January 1986 to December 2013 with eight hedging models including constant and time varying hedging models. They divided the whole periods into three sub periods: world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/2009. They found that means of hedge ratios are changing 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 could be very comparable during the Asian financial crisis. The study concludes 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 hedge ratios varying over months 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.

Awang et. al. (2014) by employing 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, reported that the OLS model performs most effectively in both index futures markets, followed by EGARCH. Based on the findings, they conclude that OLS model serves as a better hedging model than other static and time-varying models in a direct hedge using stock index futures. From the literature review above, it seems that there is no unique technique or model that can be considered as the best or superior model to estimate hedge ratios.

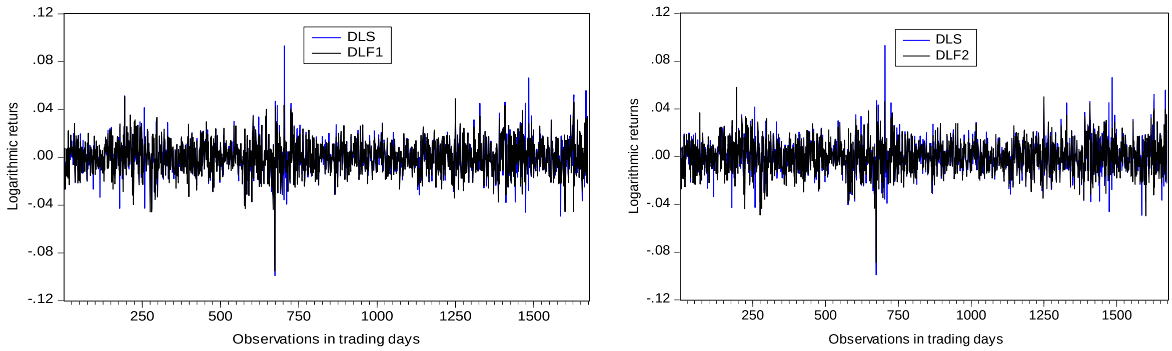
The present study applied four different models consisting of the traditional OLS model, VAR, VECM and the bivariate BEKK-GARCH models to estimate hedge ratios for two different maturity futures contracts of crude palm oil. Unlike other studies that used Malaysia Palm Oil Board (MPOB) provided data representing for CPO spot price which are collected from various regional markets, this study used FCPO spot futures as a proxy for spot CPO price and the subsequent futures prices are treated as the futures prices. CPO spot prices obtained from MPOB may not represent CPO spot prices appropriately as these prices are collected from different regional markets. This may mislead the hedging information. The study is structured as follows: In section 2, data descriptions are given while section 3 provides an overview of methodologies adopted for computing the hedge ratios and hedging effectiveness. Section 4 presents and analyses the empirical results followed by conclusion in section 5.

2. Data Description

This study employs the daily settlement prices data obtained from Bursa Malaysia Derivative (BMD) Berhad for the period from January 4, 2010 to October 31, 2017. In this study, spot month futures contract is used as a proxy for the spot price of the underlying crude palm oil and treated the subsequent futures as the futures prices (i.e., futures 1 and futures 2). The choice of selecting CPO futures spot price as a proxy for CPO spot price is based on the previous studies of Fama and French (1987), Bailey and Chan (1993), Frank and Garcia(2009), Kumar et. al. (2008). The data are transformed into natural logarithmic form and then expressed into logarithmic return. Figures (1 and 2) show the pattern of spot and futures prices expressed in natural log while figures (3 and 4) show the behavior of logarithmic returns of the prices. The return series in figures (3 and 4) indicate the pattern of volatility clustering.



Figures 1 & 2: Pattern of spot and futures prices of CPO in natural log



Figures 3 & 4: 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	-1.7693	-1.9063	ΔLS	-39.3096*	-39.3823*
LF1	-1.8216	-1.9340	ΔLF1	-40.7667*	-40.8288*
LF2	-1.8427	-1.9174	ΔLF2	-40.1741	-40.1864

*denote significance at 1% level.

2.2 Cointegration test

Cointegration test is performed by Johansen's (1988) test procedure 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 coefficients with respect to LF1 and LF2 are statistically significant for both futures. The test results are presented in table 2.2 below:

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

Hypothesized No. of CE(s)	Eigenvalue	λ_{TRACE}	95% C.V.	λ_{MAX}	95% C.V.
Futures 1					
r = 0	0.0473	84.1984*	15.4947	81.1813*	14.2646
r ≤ 1	0.0018	3.01462	3.84147	3.01462	3.84147
Futures 2					
r = 0	0.0193	35.7458*	15.4947	32.7098*	14.2646
r ≤ 1	0.0018	3.03600	3.84147	3.01462	3.84147

Note: Both *Trace* and *Max-eigenvalue* tests indicate 1 cointegrating eqn. at the 0.05 level for both futures contracts. *denotes rejection of the hypothesis at the 0.05 level.

The corresponding unrestricted cointegrating vectors normalized on *LS* are-

LS	LF1	LF2
1.000000	-1.03173	-1.05561
	(0.01266)	(0.03314)

Standard error in parentheses (.)

3. Methodology

There are a number of different econometric methods are available/proposed in the literature to compute the optimal hedge ratios. In this paper, four different competing models are employed to calculate 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-

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

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. *R*-squared obtained from the OLS regression represents the measure of hedging effectiveness.

3.2 Vector Autoregression (VAR) Method

Bivariate VAR method is used to overcome the major disadvantage of the autocorrelation in residuals exists in the OLS regression method. The optimal lag lengths chosen based on SBC criterion. The VAR model is specified as follows:

$$\Delta S_t = \alpha_s + \sum_{i=1}^{k} \beta_{Si} \Delta S_{t-1} + \sum_{i=1}^{k} \delta_{Fi} \Delta F_{t-i} + \mu_{St} \qquad (2)$$

$$\Delta F_t = \alpha_F + \sum_{i=1}^{k} \beta_{F_i} \Delta F_{t-1} + \sum_{i=1}^{k} \delta_{Si} \Delta S_{t-i} + \mu_{Ft} \qquad (3)$$

Optimal hedge ratio is calculated as-

$$h^* = \frac{\sigma_{SF}}{\sigma_F{}^2} \tag{4}$$

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 Vector Error Correction Model (VECM)

This model is applied when the underlying series in levels are non-stationary and integrated of order one $I(1)$. 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. This study employed VAR-based cointegration test of Johansen (1988) to test the cointegration and found that the series are cointegrated. The VECM specification is expressed as follows:

$$\Delta S_t = \alpha_S + \sum_{i=1}^{k} \beta_{Si} \Delta S_{t-1} + \sum_{i=1}^{k} \delta_{Fj} \Delta F_{t-i} + \lambda_S Z_{t-1} + \mu_{St} \tag{5}$$

$$\Delta F_t = \alpha_F + \sum_{i=1}^{k} \beta_{Fi} \Delta F_{t-1} + \sum_{i=1}^{k} \delta_{Si} \Delta S_{t-i} + \lambda_F Z_{t-1} + \mu_{Ft} \tag{6}$$

Where, $Z_{t-1} = S_{t-1} - \phi F_{t-1}$ is the one-period lagged error correction term, ϕ is the cointegrating coefficient, λ_S and λ_F are adjustment parameters. Optimal hedge ratio is estimated as the same way like the VAR as stated above.

3.4 Bivariate GARCH (*Diag*-BEKK GARCH)

The univariate GARCH model has been generalized to N-variable multivariate GARCH models in many ways in which the most straightforward generalization is the *vech*-GARCH initially proposed by Bollerslev, Engle 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 the bivariate GARCH (BGARCH). Some of the popular successfully applied versions of the bivariate GARCH models are the diag-*vech*-GARCH; diagl-BEKK GARCH; Constant Conditional Correlation GARCH (CCC-GARCH) and Dynamic Conditional Correlation GARCH (DCC-GARCH). This study applied diag-BEKK GARCH (1, 1) model. Baba, Engle, Kraft and Kroner (BEKK, 1995) proposed a parameterization of the *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-

$$H_t = CC' + A'\xi_{t-1}\xi_{t-1}{}'A + B'H_{t-1}B \quad (7)$$

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

$$h_{11,t} = c^2{}_{11} + a^2{}_{11,}\varepsilon_1{}^2{}_{t-1} + b^2{}_{11}h_{11,t-1} \quad (8)$$

$$h_{22,t} = c^2{}_{22} + a^2{}_{22}\varepsilon_2{}^2{}_{,t-1} + b^2{}_{22}h_{22,t-1} \quad (9)$$

$$h_{12,t} = a_{11,}a_{22,}\varepsilon_{1,t-1,}\varepsilon_{2,t-1} + b_{11,}b_{22,}h_{12,t-1} \quad (10)$$

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 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 as follows:

$$H_t = \frac{h_{12,t}}{h_{22,t}} \quad (11)$$

3.5 Measure of Hedging Effectiveness

The hedging effectiveness is defined as the proportion of the variance that is eliminated by hedging (Hull 2015; p.60). 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-

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

(12)

Where,

$Var(u) = \sigma^2 S$

(13)

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

(14)

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 is evaluated by using this measure for in-sample and out-of-sample data.

4. Empirical results

4.1 In-sample hedge ratios and hedging effectiveness

In this section, the results for 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's* are 0.8526 and 0.8532 respectively which represent as the optimal hedge ratios for two futures contracts. They are statistically highly significant and less than unity. The corresponding *R*-squared values are 0.7245 and 0.712 4 indicating reasonably good fit model. *R*-squared value measures the hedging effectiveness of the OLS model. These mean hedge ratios obtained from OLS regression provide approximately 72% and 71% reduction in the variance of the hedged position.

Table 4.1: OLS estimate results

	Coefficient	SE	*t*-statistics	*P*-values	R^2
ΔFutures 1: (β)	**0.8526**	0.012851	66.3464	0.0000	0.7245
α	9.60e-06	0.000177	0.05433	0.9567	
ΔFutures 2 :(β)	**0.8532**	0.013248	64.40098	0.0000	0.7124
α	1.44e-05	0.000181	0.079492	0.9367	

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 VAR and VECM results

Optimal hedge ratios from VAR and VECM models are calculated using equations (2 & 3). The models are estimated by choosing lag levels of 2 as selected by the lag selection criterion of SBC. First the system of equations (2 & 3) is estimated and the residuals are retrieved. These residuals are used to calculate optimal hedge ratios using equation 4 and the hedging effectiveness by using equations 12, 13 and 14. The estimate of the parameters of the spot and the futures equations (2 & 3) are not presented here to save space but available on request. The optimal hedge ratios and the hedging effectiveness calculated from VAR and VECM are presented in table 4.2 below:

Table 4.2: Optimal hedge ratios and the hedging effectiveness derived from VAR & VECM (lag = 2 chosen by SBC)

	VAR		VECM	
	ΔFutures 1	**ΔFutures 2**	**ΔFutures 1**	**ΔFutures 2**
Covariance (μ_s, μ_f) = σ_{SF}	0.000161	0.000158	0.000161	0.000158
Variance (μ_f) = $\sigma^2{}_f$	0.000187	0.000185	0.000187	0.000185
Hedge ratio (h^*) = $\sigma_{SF}/\sigma^2{}_f$	**0.862125**	**0.854261**	**0.864819**	**0.856140**
Var (u) = un-hedged	0.000185	0.000187	0.000185	0.000187
Var (h) = hedged	0.000046	0.000051	0.000045	0.000051
Hedging effectiveness (*HE*)	**0.749886**	**0.724420**	**0.754334**	**0.726958**

From the results above it can be seen that for both hedge ratios and hedging effectiveness, VECM performs better than the VAR model. Both models indicate that the nearest futures contract provide larger variance reduction as compared to the distance futures contract. This means nearest futures contract is better in hedging effectiveness. VECM however performs better than the VAR and OLS models. The efficiencies of the VAR and the VECM models are tested by means of *Q*-statistic on squared residuals series up to a lag level of 20. The test exhibited high significance for the *Q*-statistic for each lag level up to 20 suggesting the presence of autoregressive heteroscedasticity effects (the test results are not given here but available on demand).

4.1.3 Bivariate GARCH (diag-BEKK-GARCH) results

Table 4.3 presents the estimated mean hedge ratios and their effectiveness derived from the diag-BEKK-GARCH models (eqns. 8, 9 & 10).

Table 4.3: The Diag-BEKK GARCH (1, 1) results

	Diagonal BEKK-GARCH (1,1)	
	ΔFutures 1	**ΔFutures 2**
Mean (*h)**	**0.866165**	**0.859555**
Minimum (*h**)	0.044909	0.138102
Maximum (*h**)	1.103432	1.176857
Var (*u*) = un-hedged	0.000188	0.000190
Var (*h*) = hedged	0.000045	0.000050
Hedge effectiveness (*HE*)	**0.783279**	**0.759206**
S.D.	0.093743	0.096115

The estimated parameters of the diag-BEKK-GARCH models are all both plausible and statistically significant (in order to save space parameter estimates results are not presented here but available on request) for both futures contracts. The average or mean hedge ratios estimated from diag-BEKK GARCH model are higher than OLS, VAR and VECM estimated hedge ratios. Similarly the reduction of variances are also than other models as evident from table 4.3.This is true for both futures contracts. The average/mean hedge values are 0.8662 and 0.8595 for futures 1 and 2 respectively and the corresponding hedge effectiveness measures are 78.33% and 75.92% respectively. The results clearly show that both in terms of hedge ratios and the hedging effectiveness, diag-BEKK GARCH model performs better than the other models. However, there is a wide variation in the hedge ratios across the periods for both contracts 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 exhibits time varying hedge ratios. The optimal hedge ratio series obtained from the model appear to be stationary when a unit root test is conducted by using ADF test. In both cases, the null hypothesis (hedge ratio contains unit root) was strongly rejected by the data (ADF test statistics: -16.8812 and -12.7401 for diag-BEKK GARCH at 1% critical value which is -3.4341). These show that optimal hedge ratios are stable.

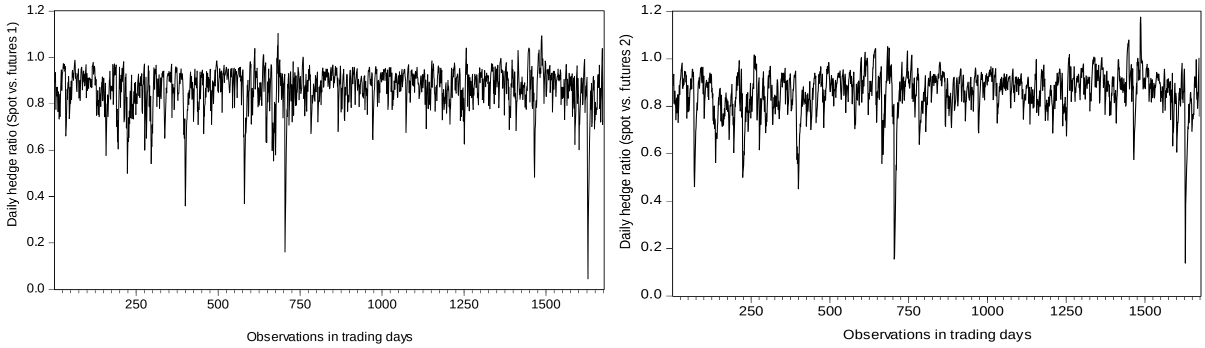


Figure 4.3: Time-varying hedge ratios estimated from diag-BEKK GARCH (1, 1) model.

Table 4.4: Comparison of optimal hedge ratios and the hedging effectiveness (HE) estimated by different models: In-sample (January 4, 2010 – October 31, 2016).

	ΔFutures 1		**ΔFutures 2**	
Models	**Variances of returns, $\sigma^2_{H,t}$**	**Variance reduction**	**Variances of returns, $\sigma^2_{H,t}$**	**Variance reduction**
Un-hedged:	0.000190	-	0.000190	-
Hedged:				
OLS	0.000052	72.45%	0.000055	71.24%
VAR	0.000046	74.99%	0.000051	72.44%
VECM	0.000045	75.43%	0.000051	72.70%
Diag-BEKK GARCH	0.000044	78.33%	0.000050	75.92%

The summary of the results presented in table 4.4 shows clearly that bivariate BEKK GARCH outperforms both in terms of estimating optimal hedge ratios and in reducing greater proportion of the variance. In terms of futures contract, the model identifies the nearest futures contract (futures 1) as the preferable one in hedging effectiveness. These results are in consistent with many other studies such as-Bailie and Myers (1991), Park and Switzer (1995), Kavussanos and Nomikos (2000), Yang (2005), Choudhry (2004), Floros and Vougas (2006), Bhaduri and Durai (2008), and Kumar et. al. (2008). 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 (You-How Go and Wee-Yeap Lau, 2014, Ong, et. al. 2012, Awang et. al. 2014) on FCPO conducted in Malaysia signifying that the crude palm oil futures market in Malaysia provides a reasonably higher level of hedging efficiency.

4.2 Out-of-the sample hedging performance

Hedging performance is also examined for out-of-sample periods which is said to be more appropriate measure as it evaluates future performance. This is due to the fact the investors are more concerned about the futures performance. For out-of-sample validation test is conducted on 1-year trading day's observations of the sample (November 1, 2016 to October 31, 2017). Hedge ratios estimated for the in sample periods 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 4.5.

Table 4.5: Out-of-sample comparisons of hedging effectiveness of different models

	ΔFutures 1		**ΔFutures 2**	
Models	**Variances of returns, $\sigma^2_{H,t}$**	**Variance reduction**	**Variances of returns, $\sigma^2_{H,t}$**	**Variance reduction**
Un-hedged	0.0001478	-	0.0001478	-
Hedged:				
OLS	0.0000307	79.25%	0.0000322	78.20%
VAR	0.0000282	80.79%	0.0000310	78.85%
VECM	0.0000276	80.86%	0.0000310	78.08%
Diag-BEKK GARCH	0.0000342	84.18%	0.0000326	77.07%

The results for out-of sample performance presented in table 4.5 are consistent with the results derived from in-sample periods. The results thus clearly show that the time varying model (the diag-BEKK GARCH) is better than the constant hedge ratio models (OLS, VAR and VECM) both in terms of producing higher optimal hedge ratios and reducing higher proportion of the risk. In other words, dynamic hedging model is preferable in hedging performance than the constant hedging models.

5. Conclusions

In this paper hedging effectiveness for two futures contracts of crude palm oil futures market traded on Bursa Derivatives Malaysia (BMD) berhad is evaluated by employing four different econometric models consisting of OLS, VAR, VECM and the bivariate GARCH (diag-BEKK GARCH) models. Both in-sample (January 4, 2010 to October 31, 2016) and out-of-sample periods (November 1, 2017 to October 31, 2017) are used for evaluation purpose. The empirical study found that dynamic hedging model (diag-BEKK GARCH) outperforms the constant hedging models both in terms of producing larger hedge ratios and reducing of larger proportion of the risk. The results are consistent for both in sample and the out-of-sample periods. The findings suggest that bivariate GARCH (diag-BEKK GARCH) model can be used as a better model to construct hedging strategy in Malaysian crude palm oil futures market. Furthermore in the financial literature, the GARCH model is also better known as able to 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 data frequency particularly based on weekly data.

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