CHAPTER 4

4.0 DATA AND METHODOLOGY

The previous chapter outlined the research framework involved in measuring the hedging performance in the CPO market. This chapter further describes the series selected for the research activity and then relates the measurement identified in Chapter 3 with the range of techniques in estimating the hedging performance consistency. The methodology section is segregated into three sub-sections consisting of diagnostic tests, mean and variance specification models and, finally, the hedging performance techniques.

4.1 DATA

The data comprises the daily settlement prices for both CPO and FCPO for the Malaysian commodity market. The CPO prices are generated from the Malaysian Palm Oil Board (MPOB), which represents the CPO spot commodity market. Meanwhile, FCPO prices are collected from the Bursa Malaysia Derivative Berhad and Bloomberg databases. The study covers the period between 2 January 1996[14]and 15 August 2008. In this study, the daily settlement prices are transformed into natural log return, which is computed as Return = 100 x [ln(P_{t+1} /P_t)], where P_{t+1} is settlement price for CPO or FCPO for period t. Next, using these returns we adopt three mean specifications,

[14] The price series were collected to cater for pre Asian Financial Crisis in June 1997 until recent global financial crisis.

namely, intercept, VAR and VECM model within GARCH volatility framework (BEKK, CCC and DCC model) in estimating the conditional mean and variance-covariance matrices for both series. Finally, using the estimated conditional mean, variance and covariances, we further proceed to measure the hedging performances using risk minimization and investor's utility function. We forecast the hedging performance within the in-sample[15] and out-sample[16] analysis for the 1, 5, 10, 15 and 20 days forecasted period ahead (similar to Yang and Allen, 2004). There is not rule of thumb to select the forecasted period ahead, hence the selection of the forecasted period is based on the researcher discretion in measuring the hedging performances.

Since its establishment in 1980, the Malaysian CPO market is considered as being the most actively traded emerging market, especially for CPO. The large sustainable global demand and growth in biodiesel technology have made Malaysia one of the world's top net exporters of CPO. Furthermore, a consistently sound policy implemented by the Malaysian government in improving the production capacity has spurred the production of vegetable oil. Referring to Table 4.1, a total of 4 million metric tonnes of palm oil was exported to China in 2007, which was 8.14% positive growth *vis-à-vis* the year before. In addition, the growth of the biofuel industry has taken the crude palm oil to another level. In late 2007, Malaysia opened its first biodiesel plant in Pahang. The plant produces 100,000 tonnes of biodiesel, 12,000 tonnes of pharmaceuticals and 4,000 tonnes of palm fatty acid distillate annually

[15] The in-sampling data period is analyzed between January 1996 and August 2008 and using the same data for in-sampling forecasting analysis.
[16] While, the out-sampling period is analyzed between January 1996 and December 2007 and reserved January 2008 to August 2008 data for out of sampling forecasting analysis.

(www.wikipedia.com). In 2007, palm oil was the largest of the world's 'oils and fats production', at 25%, while soybean oil held the second largest production market share.

Table 4.1: Malaysian Palm oil exports according to country

Region	Jan-Dec 2006	Jan-Dec 2007	Changes (%)
China/HK	3643123	3939497	8.14%
EU-27	2599616	2063226	-20.63%
Pakistan	968406	1070067	10.50%
India	561779	511167	-9.01%
USA	684651	794920	16.11%
North East*	879390	888443	1.03%
ASEAN	971622	803791	-17.27%
Bangladesh	438152	154494	-64.74%
Egypt	211686	184588	-12.80%
UAE	302738	360509	19.08%
Total Exports	**11261163**	**10770702**	**-4.36%**

* includes Japan, South Korea, North Korea and Taiwan

Source: MPOB

FCPO was the first commodity futures product introduced on Malaysia's futures commodity market. The core purpose of introducing such a product was to strengthen the commodity prices and further facilitate direct producers and buyers in managing their price risk effectively and efficiently within the local context without engaging in the international futures market The promising growth and prospect of the crude palm oil industry encouraged Bursa Malaysia in September 2008to introduce FUPA, which is a US Dollar denominated palm oil futures contract. This new futures contract was introduced to encourage more international investors to engage in the Malaysian CPO market without any currency risk exposure. Both FCPO and FUPA contracts carry a similar contract size trade of 25 metric tonne per contract. For the purpose of this research, we will only consider FCPO data not FUPA. Table 4.2 summarizes the contract specification.

Table 4.2: The FCPO contract specifications are:

Underlying Instrument	Crude Palm Oil
Contract Size	25 metric tons
Minimum Price Fluctuation	RM1 per metric ton
Daily Price Limits	With the exception of trades in the spot month, trades for future delivery of Crude Palm Oil in any month shall not be made, during any one Business Day, at prices varying more than 10% above or below the settlement prices of the preceding Business Day ("the 10% Limit") except as provided below. When at least 3 non-spot month contracts are trading at the 10% Limit, the Exchange shall announce a 10-minute cooling off period ("the Cooling Off Period") for all contract months (except the spot month) during which trading shall only take place within the 10% Limit. Following the Cooling Off Period, all contract months shall be specified as interrupted for a period of 5 minutes, after which the prices traded for all contract months (except the spot month) shall not vary more than 15% above or below the settlement prices of the preceding Business Day ("the 15% Limit"). If the 10% Limit is triggered less than 30 minutes before the end of the first trading session, the following shall apply:- a. the contract months shall not be specified as interrupted; b. the 10% Limit shall be applied to all contract months (except the spot month) for the rest of the first trading session; and c. the 15% Limit shall be applied for all contract months (except the spot month) during the second trading session. If the 10% Limit is triggered less than 30 minutes before the end of the second trading session, the 10% Limit shall be applied to all contract months (except the spot month) for the rest of the Business Day.
Contract Months	Spot month and the next 5 succeeding months, and thereafter, alternate months up to 24 months ahead
Trading Hours	First trading session: Malaysian time: 10:30 a.m. to 12:30 p.m. Second trading session: Malaysian time: 3:00 p.m. to 6:00 p.m.
Speculative Position Limits	500 contracts net long or net short for the spot month. 5,000 contracts for any single delivery month except for the spot month and 8,000 contracts for all contract months combined.

Final Trading Day and Maturity Date	Contract expires at noon on the 15th day of the delivery month, or if the 15th is a non-market day, the preceding Business Day.
Tender Period	1st Business Day to the 20th Business Day of the delivery month, or if the 20th is a non-market day, the preceding Business Day.
Deliverable Unit	25 metric tons, plus or minus not more than 2%.

Source: Bursa Malaysia Bhd

(http://www.klse.com.my/website/bm/products_and_services/derivative_resources/derivatives-fcpo.html)

4.1.1 Hedging in CPO market

The research is interested to examine the consistency of hedging performance in CPO market over the time. Therefore, the dynamic hedging strategy needs to be established, considering the information flow arrived into the market time to time. Due to this, the estimation models encompass the GARCH dynamic modelling which account for the time factor into the volatility modelling process is considered. This dynamic hedging strategy is assumed and the analysis considers a one period hedging throughout the sampling period. The model assumes that the FCPO prices is unbiased future expected CPO prices. Additionally, the CPO market participants are assumed to have a long position in spot and contrary position in futures market.[17] They will revise their hedging position daily after considering the surrounding information arrived into the market. And the research posits that hedgers will use the nearby contract FCPO prices (similar to Moschini and Myers, 2002 and Yang and Awokuse, 2002). Note that

[17] Common position held by commodities hedgers (see Ederington, 1979 to Moshini and Myers, 2002).

FCPO-3 month contact is the most actively traded futures contract, but due to missing values for few years within the sampling period, we will not consider this contract into our hedging performance analysis. Further the spot month FCPO contract is the second most actively traded, as such the study selects this contract as the proxy for CPO futures market. Another limitation of our dynamic model where the model assumed no transaction cost (the justifications have already discussed in Theoretical Framework Chapter).

4.2 METHODOLOGY

This section consists of three sub-sections that discuss the diagnostic tests, conditional mean specification and conditional second moment specification (refer to variance specification), followed by the hedging performance measurements. In the diagnostic tests section, the study will perform a statistical test to investigate the characteristics of both CPO and FCPO series. Further, three types of unit root tests will be implemented including the Augmented Dickey Filler (ADF henceforth) test, Phillip-Perron (PP henceforth) test and Kwiatkowski, Philips, Schmidt, and Shin (KPSS henceforth) test. Subsequently, the cointegration relationship between the series is detected by the Johansen Cointegration test. Then, the Ljung-Box test and correlograms of squared residual will be done to infer the existence of serial correlation and ARCH effect in the tested series. Ultimately, three structural break tests are performed to confirm if there is any regime shift in the series mean, variance and cointegration relationships.

4.2.1 Diagnostic Tests

4.2.1.1 Statistical properties

A statistical property investigation will be done to compute the series unconditional first moment (mean) and second moment (standard deviations), followed by the series unconditional third moment, which measures the asymmetry of the returns distribution around its mean. Next, its fourth moment measures the peakedness or flatness of the return distribution. Finally, the Jarque-Bera test to infer the normality of the series distribution; if there is a strong non-rejection defined in the Jarque-Bera null hypothesis.

4.2.1.2 Unit Root Tests

Much empirical evidence demonstrates that financial and economic variables behave as a random process. This random process refers to non-stationarity, which is a crucial aspect, as non-stationary will lead to a spurious normal regression estimation model. Such a spurious estimation will drive intolerance erroneous that lead to a misleading conclusion as the variance of the residual increases when the time increases. Six tests have been built to test the presence of non-stationarity of the series, namely, the Augmented Dickey Fuller, Philip-Perron, KPSS, Elliot Rothenberg Stock point optimal (ERS), Dickey Fuller test with GLS Detrending, and the Ng and Perron (NP) test. The study will adopt three unit root tests – the ADF test, PP test and KPSS test.

a) Augmented Dickey-Fuller (ADF) Test

The ADF test (1984) is a modification of the DF unit root test established by Dickey Fuller in 1979. By considering a simple AR(1) process, a Dickey Fuller test can be examined:

$$y_t = \rho y_{t-1} + x_t' \delta + \varepsilon_t \quad \textbf{(15)}$$

where : x_t' is an optimal exogenous regressor, either constant or constant with trend, ρ and δ are the parameters being estimated and ε_t is white noise.

The DF test, validates y_t as a non-stationary series when the absolute value of $\rho \geq 1$, but becomes stationary when the absolute value of $\rho < 1$. However, the ADF test seeks the presence of series non-stationary based on the following (after subtracting y_{t-1} from both sides of equation 15):

$$\Delta y_t = \alpha y_{t-1} + x_t' \delta + \varepsilon_t \quad \textbf{(16)}$$

where Δy_t is $y_t - y_{t-1}$ and α is ρ-1

The null hypothesis and alternative hypothesis may be written as:

$H_o : \alpha = 0$

$H_1 : \alpha < 0$

These hypotheses are evaluated based on the Student t-distribution. The ADF test is a powerful test that is suitable for investigating the evidence of unit root for higher order lags series in contrast to the DF test which only caters for the AR(1) model.

b) Philips-Perron Test

In 1998, Philips and Perron introduced another option for unit root measurement. It allows testing the stationary of the series using a nonparametric method of controlling for serial correlation. The PP test adopts the same ADF equation but makes an alteration on the t-ratio of the coefficient so that serial correlation will not affect the asymptotic distribution of the test statistic. The t-statistic will be based on:

$$\tilde{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0} \right)^{1/2} - \frac{T(f_0 - \gamma_0)(se(\tilde{\alpha}))}{2 f_0^{1/2} s} \qquad \textbf{(17)}$$

where $\bar{t}_\alpha$ is estimated parameter, t_α is t-ratio of the α, γ_o is consistent estimate of the error variance, se($\tilde{\alpha}$) is coefficient standard error and f_o is the estimator of the residual spectrum at frequency zero.

c) Kwiatkowski, Philips, Schmidt, and Shin (KPSS) Test (1992)

The KPSS test has a contrary null hypothesis definition compared to the ADP and PP test, where the null hypotheses shows the presence of the stationary of the series, while the alternative hypothesis infers the series has a unit root. The KPSS statistic is based on the residuals from the OLS regression of y_t on the exogenous variables x_t. While the LM test is computed based on:

$$LM = \sum_t \frac{s(t)^2}{(T^2 fo)} \qquad \textbf{(18)}$$

where fo is an estimator of the residual spectrum at frequency zero and s(t) is a cumulative residual function ($\sum_{r=1}^{t} \hat{u}_r$ where $\hat{u}_r = y_t - x_t' \hat{\delta}(0)$).

4.2.1.3 Serial Correlation Test (Ljung-Box Q-statistic Test)

It is commonly known that serial correlation and ARCH effects are identified in most financial series. The standard serial correlation test assumes that residuals have a random walk pattern and the test can detect the possibility of misspecification of a model. The Durbin Watson test was the first test developed to infer the existence of serial correlation in series. This was followed by the introduction of more advanced tests including the Box-Pierce, Lagrange Multiplier and Ljung-Box Q-statistic test. In this research, we adopted the Ljung-Box Q-statistic as the serial correlation procedure to identify whether the tested series has a white noise characteristic. The Q-statistic at lag k is a test statistic for the null hypothesis of no autocorrelation up to order k and the statistic can be calculated as follows:

$$Q_{LB} = T(T+2)\sum_{j=1}^{k} \frac{\tau_j^2}{T-j} \qquad \textbf{(19)}$$

where τ_j^2 and j-th are autocorrelation and T is the number of observations

4.2.1.4 ARCH Effect Tests

The study employed correlograms of the squared residuals to detect the presence of autoregressive conditional heteroscedasticity (ARCH) in the estimated residuals. The correlogram of squared residuals test is able to show the existence of the ARCH effect in the residuals by using the lag order derived from the Ljung-Box Q-statistics. The test indicates the absence of ARCH effect in the tested residuals in two conditions. The first condition is when the autocorrelation and partial autocorrelation are equal to zero and the second condition is when the Q-statistics are not significant.

4.2.1.5 Cointegration test

Since there are two variables involved in this research, namely, CPO and FCPO, we also test the possibility of these two series being related in the long run. We adopted the Johansen Cointegration technique to identify whether either or both series are cointegrated in the long run or not. Johansen (1995a) introduced five alternatives for cointegration identification. These include:

a) The level data y_t without any deterministic trends and no intercept in the cointegration equation.

$$H_2(r): \Pi y_{t-1} + Bx_t = \alpha\beta' y_{t-1} \qquad \textbf{(20)}$$

b) The level data y_t without any deterministic trends and an intercept in the cointegration equation.

$$H_1^*(r): \Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0) \quad \textbf{(21)}$$

c) The level data y_t with linear trends and an intercept in the cointegration equation.

$$H_1(r): \Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0) + \alpha_\perp \gamma_0 \quad \textbf{(22)}$$

d) The level data y_t and the cointegration equation with linear trends.

$$H^*(r): \Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp \gamma_0 \quad \textbf{(23)}$$

e) The level data y_t with quadratic trends and cointegration equation with linear trends.

$$H(r): \Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp(\gamma_0 + \gamma_1 t) \quad \textbf{(24)}$$

4.2.1.6 Structural Break tests

a) Structural Break test in Mean

The shift in the mean specification is identified using the Bai and Perron (1998, 2003) (BP henceforth) test. They propose a linear model with m breaks (or m+1 regimes):

(25)

$$y_t = x_t^{'}\beta + z_t^{'}\delta_j + u_t \qquad t = T_{j-1} + 1,....,T_j \text{ as } j = 1,...,m+1$$

where y_t denotes the dependent variable at period t, while x_t and z_t are vectors of covariates with dimension (p x 1) and (q x 1), respectively. Note that β and δj are the corresponding beta coefficients for x_t and z_t, respectively. Here, u_t represents the residuals at period t. The break points are treated as unknown with the convention that $T_0 = 0$ and $T_{m+1} = T$ being used. The BP test allows for testing either a partial structural change or pure structural change model. A partial structural change is one where the parameter vector β is not subject to shifts and it is estimated using the entire sample. When p=0 the model is considered a pure structural change model because all the coefficients are allowed to undergo a regime shift. The least-squares principle is employed to estimate the model.

To determine the number of breaks and their break dates, the BP test uses an efficient dynamic programming algorithm, which is discussed extensively in Bai and Perron (2003). The BP test procedure begins by testing for a single break, and then proceeds with two breaks and so forth. The optimal number of breaks (m-1) is evaluated based on the optimal break that gives the lowest sum of squared residuals.

BP (2003) also proposes another way of testing for multiple regime shifts in a series. The supF_T type test has a null of no structural break (m=0) against an alternative of a fixed number of breaks (m=k). The purpose of such a test is to allow the researcher to test for the null of no breaks against a priori knowledge on the number of breaks. In practice, the researcher may not possess any knowledge on the number of breaks and, thus, it is necessary to test for the absence of a break against some unknown number of structural breaks. In such a case, BP proposes using the double maximum tests. There are two types of double maximum test statistics; one is an equal-weight version and is referred to as a UD max $F_T(M,q)$ and the other uses a proportional weight and is referred to as WD max $F_T(M,q)$ with M=5 and $\varepsilon = 0.05$.

Finally, BP (1998) also discuss a test of m versus m+1 breaks, sup F(m+1| m), which can be used as the basis of a sequential testing procedure. They also suggest using 5 as the maximum number of fixed breaks when performing this supF test. Since the number of observations is considerably high (T=3293), we used 5% as the trimming ε value.

Based on the overall BP test result, if there is a structural change presence in both the CPO and FCPO series, we then modelled the mean equation as:

$$Rt = \alpha + D_j \qquad \textbf{(26)}$$

where R_t represents the return for CPO or FCPO and α is the mean intercept. Here D_j represents the dummy variable that accounts for the regime shift in mean for CPO and FCPO returns and it is defined as $D_j=1$ for t>Structural break date and zero otherwise.

b) Structural Breaks test in Variance

Structural breaks may not only exist in the mean series, but series unconditional variance might also experience some regime shift. To identify for a possible break in the variance of both series, we will adopt the iterated cumulative sum of squared residual algorithm (ICSS). According to Inclan and Tiao (1994) (IT henceforth), the ICSS algorithm conjectures that the second moment behaves in a monotonic fashion except when some perturbations occur to the series, which may alter the behaviour of the series to become non-stationary. The IT ICSS algorithm is able to estimate the existence of changes in variance using the following equation:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 \qquad \textbf{(27)}$$

where Ck represents the cumulative sum of squares of ε_t with ε_t comprising uncorrelated random variables that have zero mean and constant variance.

Next, the procedure proceeds to calculate the centred cumulative sum of squares (refers to D_k) using the following equation:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, k = 1,.....T, with D_0 = D_T = 0 \qquad \textbf{(28)}$$

Note that D_k will display a constant variance up to a point when changes take place in the variance. Changes in the variance capture the structural breaks in the series volatility. However, in the event that there are no breaks in the variance series the D_k

statistic will merge near to zero and vice versa. Further, the significance of those changes will be examined based on the critical value achieved from the null hypothesis of the static variance test against the alternative hypothesis of non-constant variance. A critical value of 1.36 within a 5% significant level is considered for this study. The D_k statistical test results can comfortably infer the existence of variance changes when the maximum of the absolute value of D_k is more than the critical value. Letting k* represent the $\max_k |D_k|$, when the standardization distribution of $\max_k |D_k|$ or $\max_k \sqrt{(T/2)}|D_k|$ is situated outside the predetermined boundary, we can consider k* as the turning point of variance changes. In the event of more than one change existing in the variance series, the IT ICSS algorithm is able to identify those multiple breaks via plotting the D_k.

The asymptotic distribution of IT ICSS test is calculated based on the following equation:

$$IT \Rightarrow \sup_r | W^*(r) | \qquad \textbf{(29)}$$

where W^* refers to a Brownian Bridge, while $W(r)$ represents a standard Brownian motion. And, $\Rightarrow$ is a less strong convergence indication of the related probability procedures.

One of the IT ICSS test drawbacks is where the test may detect the presence of a misleading number of structural breaks in the variance financial series. In addition, the test results may suffer some nuisance parameters and size distortion problem when the essence assumption fails to meet. To overcome this, Sanso, Arago and Carrion (2004) extended the IT ICSS algorithm and introduced the k_1 test. Similar to the IT ICSS, k_1 assumes that the residual series is an identical independent distribution with zero mean and constant variance. However, the k_1 test is able to clear the existence of nuisance parameters produced by the IT ICSS test, where k_1 is defined as:

$$k_1 = \sup_k \left| T^{-1/2} B_k \right| \tag{30}$$

where $B_k = \dfrac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}^4}}$, while $\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4$ and $\hat{\sigma}^4 = T^{-1} C_T$. However, if the residual holds the zero mean, normally, identically and independently random variable and $E(\varepsilon_t^4) \equiv \eta_4 < \infty$,thus, $k_1 \Rightarrow \sup_r \left| W^*(r) \right|$.

Considerable empirical evidence postulates that most economic and financial series have a leptokurtic distribution and some persistence in their conditional variance series. Hence, the IT ICSS and k_1 test are likely to be less appropriate since both tests assume the unconditional variance distributions to be independent and Gaussian distributed. Therefore, Sanso *et al.* (2004) introduced the k_2 test that is able to address the fat tails and persistency problem in those series. The adjusted statistic encompasses:

$$k_2 = \sup_k \left| T^{-1/2} G_k \right| \tag{31}$$

where $G_k = \hat{\omega}_4^{-1/2} (C_k - \frac{k}{T} C_T)$ **(32)**

The k_2 test is able to solve both problems by clearly imposing the conditional heteroscedasticity and the disturbance's fourth moment properties via non-parametric adjustment based on the Bartlett kernel. Refer to equation 32, $\hat{\omega}_4$ is a consistent estimator of ω_4 and the non-parametric estimator of ω_4 defined as follows:

$$\hat{\omega}_4 = \frac{1}{T}\sum_{t=1}^{T}(\varepsilon_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T}\sum_{l=1}^{m}\omega(l,m)\sum_{t-1}^{T}(\varepsilon_t^2 - \hat{\sigma}^2)(\varepsilon_{t-1}^2 - \hat{\sigma}^2) \quad \textbf{(33)}$$

where $\omega(l,m)$ represents the lag window and this lag window refers to the quadratic spectral $[1 - l/(m+1)]$. The bandwidth m is selected by Newey-West (1994) techniques. If the general assumption is satisfied, the k_2 test will produce the same asymptotic distribution as in the IT ICSS test and, further, construct a finite sample critical value.

Referring to Sanso *et al.* (2004), they recommend the k_2 test as a powerful structural break test for variance. It is said that the test results are free from any size distortion and the procedure gives a more reliable number of breaks than the IT and k_1 test. In addition, the non-normality features in most financial series may influence both IT and k_1 to give a less accurate number of structural breaks than exist in these series variance. Hence, this study will implement the IT, k_1 and k_2 techniques to infer the presence of potential structural breaks in both CPO and FCPO returns. We then compare these three tests results and choose which test gives more sensible structural changes in both returns.

c) Structural Breaks Cointegration Test

There is ample empirical evidence to suggest that most spot and future returns are cointegrated (Kroner and Sultan, 1993; Floros and Vougas, 2004). As will be shown in the next section, given that both CPO and FCPO returns display structural breaks in their mean and variance, it is possible that the cointegration relationship between them may undergo a regime change too. Gregory and Hansen (1996) developed a test that allows identifying any regime shift presence in the long run relationship between the two variables. Contrary to Zivot and Andrews (1992), Perron (1997) and Lumsdaine and Papell (1997), the test focuses on the regime shift in the cointegration relationship, while the three procedures test the existence of regime shift within the random walk hypothesis. The GH-Cointegration test comprises three models that permit testing within level shift (without trend), level shift with trend and regime shift (structural changes in both level and slope coefficient). The level shift model is given by:

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha y_{2t} + \varepsilon_t, t = 1,,n, \qquad \textbf{(34)}$$

where y_{1t} and y_{2t} are observed variables and y_{1t} is real valued. While, y_{2t} is an m-vector and stationary at first different. ε_t represents the residuals and stationary at level. μ_1 and μ_2 are the intercept and intercept dummy coefficient. And, $\varphi_{t\tau}$ denotes an interaction intercept dummy with $\begin{Bmatrix} 0,....t \leq [n\tau] \\ 1,....t > [n\tau] \end{Bmatrix}$.$\tau$ is the unknown parameters, which take the value of either 1 or 0. This value shows the turning point of the long run relationship between the observed variables and [ ] refers to the integer part.

Second, the GH-Cointegration model allows for the level shift with trend. The model is estimated as follows:

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha y_{2t} + \beta t + \varepsilon_t, t = 1,, n, \quad \textbf{(35)}$$

where t represents the trend and β represents the beta coefficient for trend.

Finally, the third model (regime shift) encompasses:

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha_1 y_{2t} + \sigma_2 y_{2t} \varphi_{t\tau} + \beta_1 t + \beta_2 t \varphi_{t\tau} + \varepsilon_t, t = 1,, n, \quad \textbf{(36)}$$

where μ_1, β_1 and α_1 are the intercept, trend coefficient and slope coefficient prior structural shift. Meanwhile, μ_2, β_2 and α_2 are the intercept, trend coefficient and slope coefficient post structural shift, and $t\varphi_{t\tau}$ is the slope interaction dummy.

4.2.2 Conditional Mean and Variance Specification

Thus far, the previous section discusses the preliminary tests confirming the characteristics of both series and the suitability of the non-linearity modelling procedure that can be implemented into both series. Most literature exhibits the non-normality characteristic in most financial series, hence, it is valid to model the series return mean and variance using the GARCH framework. In addition, the GARCH framework allows estimating of both the series variance and covariance structures and indirectly can generate the time varying hedging ratios (conditional covariance between spot and futures divided by conditional variance of FCPO). This section proceeds to elaborate on the non-normality modelling procedure undertaken throughout the research. The section begins with the three different mean specifications – intercept, VAR and VECM model. Then, we discuss the conditional second moments (variance and covariance) for both series using BEKK, Conditional Constant Correlation and Dynamic Conditional Correlation model. Next, a modified BEKK model that caters for structural breaks (if any) in both the mean and variance specification is explained. Finally, the section ends with the hedging performance forecasting in both performance measurements.

4.2.2.1 Modelling Conditional Mean Specifications

The most straightforward way to model the conditional mean is through regressing the return with its constant. A similar mean specification was adopted by Baillie and Myers (1991) in six commodities markets and Ford, Pok and Poshakwale (2005) in the Malaysian Stock Index Futures market. The intercept model is defined as follows:

a) Intercept

$$r_{st} = \alpha_s + \varepsilon_{st}\,;\ \varepsilon_{st} \left| \Omega_{t-1} \right. \sim N(0,H_t) \qquad \textbf{(37)}$$

$$r_{ft} = \alpha_f + \varepsilon_{ft}\,;\varepsilon_{ft} \left| \Omega_{t-1} \right. \sim N(0,H_t) \qquad \textbf{(38)}$$

where r_{st} and r_{ft} denote as the return for spot and futures , Ω_{t-1} defines the past information at period t-1, α is the constant and ε is the residual series.

b) Vector Autoregressive

The vector autoregressive modelled the return including both the spot and futures returns lagged term. The model is able to recognize the short-term association between spot and future returns . The model is specified as follows:

$$r_{st} = \alpha_s + \sum_{i=1}^{k} \alpha_{s1} r_{s,t-i} + \sum_{i=1}^{k} \alpha_{f1} r_{f,t-i} + \varepsilon_{st} \qquad \textbf{(39)}$$

$$r_{ft} = \alpha_f + \sum_{i=1}^{k} \alpha_{f2} r_{f,t-i} + \sum_{i=1}^{k} \alpha_{s2} r_{s,t-i} + \varepsilon_{ft} \qquad \textbf{(40)}$$

where α_s and α_f denote the constant term, α_{s1} , α_{f1} , α_{s2} and α_{f2} are parameters. ε_{st} and ε_{ft} residuals, which are independently identically distributed random vectors. And the above model testable hypothesis is:

H_0 : There is no association between CPO and FCPO returns

H_1: There is an association between CPO and FCPO returns

c) Vector Error Correction model

However, a long term relationship can be determined by including the error term, which represents the evidence of long run deviating equilibrium in both spot and futures returns. When both series are integrated at 1 or stationary at its first difference, there is a tendency of both series to be cointegrated in the long run. Engle specifies that the cointegration test can be performed through two-stage tests, however, Johansen simplifies the cointegration test via the Johansen Cointegration test. The long run equilibrium between the spot and futures return can be tested by including the error term in VAR model (VECM). The VECM is expressed as follows:

$$r_{st} = \alpha_s + \sum_{i=1}^{k} \alpha_{s1} r_{s,t-i} + \sum_{i=1}^{k} \alpha_{f1} r_{f,t-i} + e_s Z_{t-1} + \varepsilon_{st} \quad \textbf{(41)}$$

$$r_{ft} = \alpha_f + \sum_{i=1}^{k} \alpha_{f2} r_{f,t-i} + \sum_{i=1}^{k} \alpha_{s2} r_{s,t-i} + e_f Z_{t-1} + \varepsilon_{ft} \quad \textbf{(42)}$$

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

H_0: There is no association between the ECM and the series mean return.

H_1: There is an association between the ECM and the series mean return.

4.2.2.2 Modelling Conditional Variance Specifications

a) BEKK Model

To overcome the non-positive definiteness parameters estimated by the VECH model, Baba, Engle, Kraft and Kroner (1990) developed a model that allows capturing the behaviour of the conditional variance and covariance and maintaining the positive definiteness of parameters estimated. For the purpose for this research, we adopted the modified BEKK model that was introduced by Engle and Kroner in 1995. A general modified BEKK model is encompassed within a basic GARCH (1,1) model and the model defines the H_t as follows:

$$H_t = C^{*'} C^* + \sum_{k=1}^{K} A_k^{*'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_k^* + \sum_{k=1}^{K} G_k^{*'} H_{t-1} G_k^* \qquad \textbf{(43)}$$

where C* $= \begin{bmatrix} c_{ss} & c_{sf} \\ 0 & c_{ff} \end{bmatrix}$, $A_k^* = \begin{bmatrix} a_{ss} & a_{sf} \\ a_{fs} & c_{ff} \end{bmatrix}$ and $G_k^* = \begin{bmatrix} g_{ss} & g_{sf} \\ g_{fs} & g_{ff} \end{bmatrix}$.While, $\varepsilon_t = \begin{bmatrix} \varepsilon_{ss} \\ \varepsilon_{ff} \end{bmatrix}$ and $H_t = \begin{bmatrix} H_{ss} & H_{sf} \\ H_{fs} & H_{ff} \end{bmatrix}$. K is the summation limit, which determines the model generality and K is assumed to be 1. However, Engle and Kroner (1995) specified that the BEKK model is generally sufficient when K is assumed as a large number. With K >1, it can retain the positiveness of the estimated parameters (coincide for all of DVEC parameters and most of the parameters for the VEC model).

Engle and Kroner (1995) further specified that a fully generalized GARCH (1,1) BEKK model can be achieved by fulfilling the two conditions below, first when *"Assuming s = (N(N+1))/2 while a large number of K need to consider so that the total of* s^2 *distinct parameters in* A_k^* *and* G_k^* *matrices."* and second *" define* $a_{ij,k}^*$ *to be ijth element of non zero* $A_{ij,k}^*$ *(* $A_{ij,k}^*$ *represents either in* $a_{il,k}^*\ a_{jm,k}^*$ *or* $a_{jl,k}^*\ a_{im,k}^*$ *) between 1 and N. The second condition similarly applies to* G_k^* *matrices.*

Assuming there is a bivariate full general GARCH (1,1) model, there will be 18 distinct parameters for A_k^* and G_k^* for the parameter estimation, which is noticeably unable to meet the condition set by Engle and Kroner. In addition, it is not easy to deal with a large number of parameters, therefore, we can reduce the number of estimated parameters by imposing a diagonal BEKK model. The Diagnoal BEKK is a lesser general version of the DVEC model and the parameters estimated from the model are fewer (7 parameters) than the Bivariate DVECH model (9 parameters), as the covariance estimation is simultaneously produced by two variance equations in the same model. It is expected that when K is assumed to be large, there will be no restriction imposed in A_k^* matrices. Hence, some of A_k^* will produce a similar matrices structure, consequently, an identification problem will occur. To overcome this, when K>1 we need to include some restriction on A_k^* matrices. As part of this restrictive BEKK model, the research will adopt a more general BEKK model with K=1 because of the high insurability of the positive definiteness without any additional limitation imposed on A_k^* and G_k^*.

b) Constant Conditional Correlation model

Bollerslev (1990) developed a basic and simple condition correlation model using the normal univariate GARCH framework. The model defined is based on the following specification:

Condition covariance matrix

$$Ht = Dt\, P\, D_t \tag{44}$$

where D_t is diag($(h_{1t}^{1/2},.....,h_{Nt}^{1/2})$ and P = [ρij] is positive definite with ρii =1. i=1,….N.

Off Diagonal elements for conditional covariance matrix

$$[H_t]_{ij} = h_{it}^{1/2} h_{ij}^{1/2} \rho_{ij} \;\; i \neq j \text{ or } \sigma_{sft} = \rho \sigma_{st} \sigma_{ft} \tag{45}$$

where $1 \leq i, j \leq N$

Conditional variances model (univariate GARCH process)

$$\sigma_{st}^2 = \gamma_s + \sum_{j=1}^{p} \alpha_s \sigma_{s,t-1}^2 + \sum_{j=1}^{q} \theta_s \varepsilon_{s,t-1}^2 \tag{46}$$

$$\sigma_{ft}^2 = \gamma_f + \sum_{j=1}^{p} \alpha_f \sigma_{f,t-1}^2 + \sum_{j=1}^{q} \theta_f \varepsilon_{f,t-1}^2 \tag{47}$$

where γ, α, and θ are all positive, assuming $\alpha_i + \theta_i \leq 1$ for i= s,f. However, the second moments of variance and covariance for both spot and futures are time varying and ρ to be constant.

Bollerslev (1990) assumes that the correlation is time in-varying and can be estimated by using the standardized residual of spot and futures return. Meanwhile, the maximum likelihood estimate of the correlation matrix is equal to the positive semi-definite sample correlation matrix. Therefore, the conditional variance is positive definite if both conditional variance-covariance matrixes are positive semi-definiteness. Bollerslev further outlines that the conditional variance specification follows a univariate GARCH process where α_i follow a GARCH process (long run persistence shocks to return i) and θ_i follows the ARCH process indicating short run persistence shocks to return i. Note that the model does not cater for the identification of asymmetric term as it is a parsimony model where the constant conditional correlation restriction is able to reduce the number of unknown parameters.

c) Dynamic Conditional Correlation Model

In reality, it is less accurate for researcher to posit a monotonic conditional correlation in many economic and financial variables. Consequently, Tse and Tsui (2002) and Engle (2002) introduced the latest development in time varying conditional correlation GARCH models, namely, Dynamic Conditional Correlation (DCC). The model is able to capture time varying correlation between two random returns. For the purpose of this research, the Engle's DCC model will be used, where the model is outlined according to the following requirement:

$$Ht = D_t \, P \, D_t \qquad \textbf{(48)}$$

where D_t is the diag($(h_{1t}^{1/2},.....,h_{Nt}^{1/2})$ and P follows the dynamic process (contrary to Constant Correlation model where p is set to constant).

$$P_t = diag(q_{11,t}^{-1/2},....q_{NN,t}^{-1/2})Q_t diag(q_{11,t}^{-1/2},....q_{NN,t}^{-1/2}) \quad \textbf{(49)}$$

where the N x N is a symmetric positive definite matrix $Q_t = (q_{ij,t})$ and Q_t formulates as follows:

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1}u_{t-1}^{'} + \beta Q_{t-1} \quad \textbf{(50)}$$

where u_t represents the standardized residual ($\varepsilon_{it} / \sqrt{h_{ij}}$) , $\overline{Q}$ is the N x N unconditional correlation matrix of standardize u_t , and α and β are the non-negative scalar parameters, which are restricted to be $\alpha + \beta < 1$.

The Qt matrix is written similar to the GARCH process and transformed into a matrix. However, a constant conditional correlation can be tested by restricting $\alpha = \beta = 0$ towards the DCC model. This model, however, tends to drive the conditional correlation to similar dynamics because α and β are scalars. On the other hand, when the N is large, the model becomes easy and flexible to use because the model can be estimated through the two-step process; however, the coefficient is not easy to interpret.

d) Modified-BEKK Model

To investigate the implications of structural breaks in the volatility clustering estimation process, the study will consider the intercept mean specification and BEKK model developed by Engle and Kroner (1995), which allows capturing the behaviour of the conditional variance and covariance in two variables simultaneously (refer to equation 43). The BEKK-GARCH model without Structural Break will be estimated, followed by, the modified BEKK model that allows for the presence of any structural breaks in the tested series (if any). The model can be estimated:

$$Y_t = \alpha_0 + \alpha_1 MD_t + \varepsilon_t, \qquad \varepsilon_t \mid I_{t-1} \approx N(0, H_t) \tag{51}$$

$$H_t = C^{*'}C^{*} + \sum_{k=1}^{K} A_k^{*'}\varepsilon_{t-1}\varepsilon_{t-1}^{'}A_k^{*} + \sum_{k=1}^{K} G_k^{*'}H_{t-1}G_k^{*} + \sum_{k=1}^{K} C1_k^{*'}D1_t C1_k^{*} \tag{52}$$

where MD_t is a the dummy break in the mean equation, while, $D1_t$ is equal to 1 if t>k and zero otherwise, k equals the date of the break in the conditional mean (based on the breaks date given in BP tests). While, $D1_t$ refers to the dummy variables in variance (the structural break date will be based on ICSS tests results). And C1* is the N x N matrices that represent the coefficient for the dummy variables for structural breaks (if any). Based on the structural break effect (MD_t), the above model (refer to equation 51) wish to test:

H_0 : Structural break does not affect the CPO and FCPO mean

H_1 : Structural break does affect the CPO and FCPO mean.

However to test the break effect ($D1_t$) against the tested series volatility, the equation 52 is testing the following hypothesis:

H_0: Structural break does not affect the CPO and FCPO volatility

H_1 : Structural break does affect the CPO FCPO volatility.

4.2.3 Hedging Performance Measurement

Based on chapter 2, there are two paradigms to evaluate hedging effectiveness, namely, a simple minimum variance paradigm and reasonable complex mean variance paradigm. The research will implement both paradigm measurements to realize the research objectives (in Chapter 1). According to Ederington (1979), hedging effectiveness can be derived from measuring the risk reduction attained by hedgers as compared to non-hedgers. The variance in both spot and futures markets is a proxy for both unhedged and hedged portfolios. The unhedged portfolio can be computed as follows:

$$VAR(UNHE) = X_s^{\ 2}\sigma_s^{\ 2} \quad \textbf{(53)}$$

where *VAR(UNHE)* represents the variance for the unhedged position and σ_s^2 is the variance for spot return. Since X_s^2 assumes to be equal to one, the variance of unhedged portfolios will be equal to the variance for spot return.

The variance for hedging position (combining the risk factor presence in both spot and futures market) can be computed as follows:

$$VAR(HE) = X_s^{\ 2}\sigma_s^{\ 2} + X_f^{\ 2}\sigma_f^{\ 2} - 2X_s X_f \sigma_{sf} \quad \textbf{(54)}$$

where *VAR(HE)* refers to the variance for hedge position, X_s^2 and X_f^2 represent the number of contracts held for spot and futures market, σ_f^2 represents the variance for future return and σ_{sf} is the covariance between spot and future return. As we assume the number of spot contracts is equal to one, the variance of hedging portfolio is $VAR(HE) = \sigma_s^{\ 2} + h^2\sigma_f^{\ 2} - 2h\sigma_{sf}$ where h represents the optimal futures contracts held against the spot contracts (also known as MVHR). Finally, the hedging effectiveness can be computed as follows:

$$HE = [1 - Var(HE)^*/Var\,(UnHE)] = \rho^2 \qquad \textbf{(55)}$$

where the hedging effectiveness is equal to the squared correlation between the spot and future returns.

Another hedging performance measurement is through the utility maximization function comparison. The investor's utility maximization function is calculated by comparing the mean return with the variance attained for each investment strategy, while considering the investors level of risk aversion. Although this research is not interested in estimating the best utility maximization that could be attained by hedgers, it is interested in identifying the significant changes in investor's utility maximization when different mean and variance specifications are adopted (at given range of level risk aversion). Gagnon *et al.* (1998) lay out the utility maximization of each investor, which can be identified as follows:

$$\underset{h}{MAX} = \left\{E(RH_t \middle| \Omega_{t-1}) - 1/2\phi VAR(RH_t \middle| \Omega_{t-1})\right\} \qquad \textbf{(56)}$$

where the RH_t is equal to the return of the hedging portfolio ($r_s - hr_f$), Ω_{t-1} defines as the surrounding information at period t-1, Φ is the risk tolerance considered by investors and $VAR(RH_t)$ representing the variance of hedging portfolio. Similar measurement was demonstrated by Yang and Allen (2004) in the Australian stock index futures hedging performance.