CHAPTER 5

5.0 FINDINGS

This chapter presents the findings and further discusses the analysis of the results generated from the selected methodology in the previous chapter. The chapter is segregated into three sections consist the preliminary analysis, model selection and finally, the structural break effect in the consistency of hedging performance measurement. In the first sub section, the research discusses the statistical characteristic of both CPO and FCPO series. Additionally, in the second section, the chapter proceeds to seek the best dynamic model that will give the best hedging performance result. The analysis compares nine dynamic models encompass the GARCH framework within the mean-variance and minimum variance measurement. Using the dynamic model selected this second sub section, the next section will introduce the structural break effect which possibility could affect the hedging performance results. Finally, the third section will then relates the structural break effect with the consistency of hedging performance results within the whole research period.

SECTION I

5.1 PRELIMINARY ANALYSIS

5.1.1 Descriptive Statistic Results

Table 5.1: Statistical Properties for CPO and FCPO returns

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
CPO	0.0184	0.0000	15.2925	-14.0783	1.5019	-0.0805	16.3897

	Jarque-Bera	Q(9)	Q(15)	$Q^2(9)$	$Q^2(15)$
CPO	24603.05	19.707	40.272	505.98	575.93
	(0.0000)	(0.012)	(0.0000)	(0.0000)	(0.0000)

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
FCPO	0.0196	0.0000	13.8469	-10.016	1.6200	0.2265	9.5267

	Jarque-Bera	Q(9)	Q(15)	$Q^2(9)$	$Q^2(15)$
FCPO	5872.988	25.332	30.779	446.84	600.81
	(0.0000)	(0.001)	(0.0000)	(0.0000)	(0.0000)

P-value are provided in parentheses for Jarque-Bera, Q(9), Q(15), Q^2 (9) and Q^2 (15).

Table 5.1 summarises the statistical properties of CPO and FCPO returns for the period of January 1996 to August 2008. The CPO has a wider range of returns ranging between -14.07% and 15.29% compared with the FCPO, which ranges between -10.01% and 13.84%. The FCPO returns, on the other hand, exhibit a slightly higher standard deviation than the CPO returns. Both returns show a non-symmetric distribution, with the FCPO (CPO) returns distribution being positively (negatively) skewed. Both returns series exhibit an excess kurtosis. The non-normality feature in both returns series is found in the Jarque-Bera test results. Such a feature is consistent with many other financial and commodity returns (see Baillie and Myers, 1991; Kroner and Sultan, 1993 and Ford, Pok and Poshakwale, 2005).

The Q statistic for the residuals and squared residuals were done at lagged 9 and lagged 15. Similar results were reported in the CPO and FCPO returns (Liew and Brooks, 1998 and Azizan *et al.*, 2007) with both being lagged, inferring the presence of serial correlation, and an autoregressive and heteroscedasticity problem. These results also tally with the evidence documented in other markets including Mili and Abid (2004) in the Canadian Bankers Acceptance returns, Yang and Allen (2004) in the Australian Stock Index returns and Ford, Pok and Poshakwale (2005) in the Malaysian Stock Index returns. In contrast, Bailie and Myers (1991) failed to find the presence of any serial correlation problem in Beef, Coffee, Corn, Cotton, Gold and Soybeans commodity prices. In sum, the non-normality features and the presence of both serial correlation and ARCH effect in both series unanimously prove the importance of considering the surrounding information in modelling both returns.

5.1.2 Unit Root Test Results

The usage of the unit root test confirming the evidence of stationarity in times series is said to be less adequate. Consequently, the KPSS stationary test is tailored to complement the other unit root statistical test (DF test or PP test) in determining the stationarity of the series. Thus, the research adopted both the ADF test and the PP test to test both CPO and FCPO series unit root, while the KPSS test is to identify the series stationarity. Testing both unit root and stationarity hypothesis may give a strong conformation whether the series are stationary or integrated (Kwiatkowski *et al*, 1992). Many recommend including both tests to strengthen the conclusion of the presence of stationarity in the tested time series.

Table 5.2: Unit Root Tests Results

	ADF Test		**PP Test**		**KPSS Test**	
	Level	**1st Diff**	**Level**	**1st Diff**	**Level**	**1st Diff**
CPO	-1.0155	-51.6597	-1.3147	-53.3742	1.8101	0.1079
	(0.7498)	(0.0001)	(0.6249)	(0.0001)	(0.0000)	(0.4809)
FCPO	-0.8899	-56.3109	-1.2598	-57.3597	1.8778	0.1148
	(0.7920)	(0.0001)	(0.6503)	(0.0001)	(0.0000)	(0.4872)

P-values are provided in parentheses for these three tests.

Table 5.2 illustrates the results for the unit root test employed for CPO and FCPO. Previous researchers employed the ADF and PP tests for both spot and futures returns, and they supported the non-stationary characteristic in the tested series (Kroner & Sultan, 1993; Tong, 1996; Bera, Gracia & Poh, 1997; Liew and Brooks, 1998; Brails *et al.*, 2002; Brooks, Hendry & Persand, 2002; Chen *et al*, 2002; Tunara & Tan, 2002; Floros and Vougas, 2004, Ford, Pok and Poshakwale, 2005; Norden, 2006; and Azizan *et al.*, 2007). The ADF and PP test results indicate that these two series virtually unanimously fail to reject the null hypothesis where the series have a unit root at level [integrated at 0 or I(0)]. Such results validated a non-stationary characteristic in these variables at any 10%, 5% and 1% significant level. Contrary results were portrayed when the series was taken at its first different or integrated at 1 [I(1)]. In addition, the KPSS test reports a rejection of its null hypothesis where the series is stationary. The rejections drive the same conclusion for both the ADF and PP tests. On the other hand, when examining the series at its first difference, we tend to accept the KPSS null hypothesis. Overall, these three tests infer a strong non-stationarity of series at its level but which turned to be stationary at its first different.

As the unit root tests support that the series are stationary at its first different (I(1)), we can safely conjecture the possibility of both series being cointegrated in the long run. As such, we test the cointegration relationship within both series via the Johansen Cointegration Test and the results are reported in Table 5.3. The results obviously exhibit a long run relationship between both series at the 5% level of significance. Generally, these unit root test results indicate the need of series transformation for the hedging effectiveness modelling process. Consequently, these CPO and FCPO settlement prices are transformed into returns and these computed returns are stationary at its level.

Table 5.3: Johansen Cointegration Test Results

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.054721	186.3361	15.49471	0.0001
At most 1	0.000379	1.246259	3.841466	0.2643

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.054721	185.0898	14.26460	0.0001
At most 1	0.000379	1.246259	3.841466	0.2643

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

SECTION II

5.2 DIVERSE MEAN AND VARIANCE SPECIFICATIONS versus HEDGING PERFORMANCES

Conclusive evidence indicates that the hedging decision is a dynamic process rather than a static process. The hedging contract effectiveness, which often refers to the degree of variance (risk proxy), can be further reduced when market participants include hedging in their investment decision. Empirical evidence tests a diverse range of dynamic models that aim to estimate the variance and covariance structure and further determine which model tends to produce the largest risk reduction. However, the evidence is mainly from the examination of developed futures markets. As part of risk reduction the investor utility maximization is actually equally important as it covers the risk and return, however, only a few researchers investigate both.

Since Lien (2004) finds that the omission of long run equilibrium in mean specification may give a downward bias hedging ratio, we believe that a different mean specification will generate various hedging performance results. To address this issue, this research moves the attention of variance-covariance structure specification to vary mean returns modelling specification and investigates its implication on hedging performance. The research adopted the intercept, vector autoregressive and vector error correction term mean specification for the BEKK, Constant Correlation and Dynamic Conditional Correlation models. These nine models were used to estimate the variance and covariance in the Malaysian Palm Oil Commodity markets. Subsequently, the research analysed the hedging performance using both the risk reduction and utility maximization function. The performances are tested within in-sample and out-sample multiple forecasting periods (1, 5, 10, 15 and 20 days).

5.2.1 Maximum Likelihood Estimation Results

Table 5.4: Maximum Likelihood estimation results for the BEKK, CCC and DCC models.

	BEKK			CCC			DCC		
	Intercept	**VAR**	**VECM**	**Intercept**	**VAR**	**VECM**	**Intercept**	**VAR**	**VECM**
					Mean Specification				
α_{0s}	-0.0137	0.0111	0.0024	-0.0167	-0.0125	-0.0125	-0.0097	-0.0064	-0.00558
α_{0f}	-0.0195	0.0156	-0.0258	-0.0068	-0.0045	0.0036	-0.0035	0.00301	0.0014
α_{1st-1}		-0.2028***	-0.1386***		-0.1797***	-0.1156***		-0.1801***	-0.1194***
α_{1st-2}		-0.1342***	-0.1281***		-0.1498***	-0.0896***		-0.1484***	-0.0932***
α_{1st-3}		-0.0905***	-0.0404*		-0.0937***	-0.0396*		-0.0894***	-0.0399*
α_{1st-4}		-0.0342	0.00436		-0.0511**	-0.00287		-0.0369*	0.0078
α_{1st-5}		-0.0092	0.0419**		-0.0397**	0.0136		-0.0181	0.0349*
α_{1st-6}		-0.0108			-0.0239			-0.0137	
α_{1ft-1}		0.3945***	0.3208***		0.3682***	0.302***		0.38***	0.3185***
α_{1ft-2}		0.191***	0.1592***		0.2015***	0.1422***		0.2072***	0.1523***
α_{1ft-3}		0.1024***	0.0807***		0.1065***	0.048**		0.0999***	0.0435**
α_{1ft-4}		0.0528*	0.022		0.048**	-0.0005		0.0408**	-0.0048
α_{1ft-5}		0.03779*	-0.0291		0.0542***	0.0094		0.0431***	0.0011
α_{1ft-6}		0.0424*			0.0646***			0.0677***	
e_s			-9.8826***			-8.3281***			-7.8179***
α_{2ft-1}		-0.1205***	-0.0744**		-0.1473***	-0.0552**		-0.1435***	-0.0483*
α_{2ft-2}		-0.1081***	-0.0329		-0.1176***	-0.0333		-0.1118***	-0.0301
α_{2ft-3}		-0.1393***	-0.031		-0.1216***	-0.0556**		-0.1283***	-0.0617***
α_{2ft-4}		-0.1237***	-0.0235		-0.1397***	-0.0755***		-0.1461***	-0.0789***
α_{2ft-5}		-0.1092***	-0.0179		-0.0986***	-0.0379*		-0.0972***	-0.0303
α_{2ft-6}		-0.0876***			-0.0651***			-0.0705***	
α_{2st-1}		0.2162***	0.1385***		0.2453***	0.1572***		0.2382***	0.1503***
α_{2st-2}		0.1762***	0.0747**		0.1691***	0.0936***		0.1719***	0.0951***
α_{2st-3}		0.1444*	0.0671**		0.1454***	0.0777***		0.1478***	0.0774***

α_{2st-4}		0.1475***	0.0541**		0.1395***	0.0757***		0.1465***	0.0792***
α_{2st-5}		0.1057***	0.0137		0.0705***	0.0151		0.0899***	0.0281
α_{2st-6}		0.0879***			0.074***			0.0775***	
e_f			7.254***			10.6795***			10.7573***

		BEKK			**CCC**			**DCC**	
	Intercept	**VAR**	**VECM**	**Intercept**	**VAR**	**VECM**	**Intercept**	**VAR**	**VECM**
	Variance-Covariance Specification								
C_s	0.2293***	0.1943***	-0.2512***	0.0615***	0.0402***	0.0393***	0.0622***	0.0402***	0.036***
C_{sf}	-0.1461***	0.1392***	0.3664***	0.5341***	0.5971***	0.6067***			
C_f	-0.601-E6	0.87-E6	-0.1873-E5	0.0432***	0.0481***	0.0507***	0.0497***	0.0508***	0.0504***
A_s	-0.3111***	-0.2568**	-0.5893***						
A_{sf}	-0.0633	0.04931	-0.0191						
A_{fs}	-0.1769***	-0.1017	0.2807**						
A_f	-0.0273	-0.2604***	-0.2554*						
G_s	-0.5669***	-0.1319***	-0.2492						
G_{sf}	0.4643***	-0.4375***	0.0535**						
G_{fs}	-0.3850***	0.3253***	0.8648***						
G_f	-1.1543***	-0.6701***	0.5346**						
A_s				0.8482***	0.8846***	0.8869***	0.8479***	0.8803***	0.8848***
A_f				0.9313***	0.9187***	0.9153***	0.9215***	0.9107***	0.9063***
B_s				0.1299***	0.0974***	0.09503***	0.1353***	0.111***	0.1075***
B_f				0.0487***	0.0584***	0.06077***	0.0594***	0.0716***	0.07546***
a							0.0771***	0.1152***	0.1096***
b							0.6758***	0.6679***	0.6622***

*** represents 1 % level of significance

** represents 5 % level of significance

* represents 10 % level of significance

This table reports joint maximum likelihood estimates of the conditional means and the covariance matrix of the returns of CPO and FCPO for the following specification:

Mean Specification

Constant

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

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

VAR

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

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

VECM

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

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

Variance Specification (BEKK)

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

Variance Specification (CCC)

$$H_t = \begin{bmatrix} h_{ss,t} & h_{sf,t} \\ h_{sf,t} & h_{ff,t} \end{bmatrix} = \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix}$$

$$h_{st} = \gamma_s + \sum_{j=1}^{p} A*_{11}\, h_{s,t-1} + \sum_{j=1}^{q} B*_{11}\, \varepsilon_{s,t-1}^{2}$$

$$h_{ft} = \gamma_f + \sum_{j=1}^{p} A*_{22}\, h_{f,t-1} + \sum_{j=1}^{q} B*_{22}\, \varepsilon_{f,t-1}^{2}$$

$$h_{sft} = \rho\sqrt{h_{st}}\sqrt{h_{ft}}$$

Variance Specification (DCC)

$$H_t = \begin{bmatrix} h_{ss,t} & h_{sf,t} \\ h_{fs,t} & h_{ff,t} \end{bmatrix} = \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix} \begin{bmatrix} 1 & Q_t \\ Q_t & 1 \end{bmatrix} \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix}$$

$$h_{st} = \gamma_s + \sum_{j=1}^{p} A*_{11}\, h_{s,t-1} + \sum_{j=1}^{q} B*_{11}\, \varepsilon_{s,t-1}^{2}$$

$$h_{ft} = \gamma_f + \sum_{j=1}^{p} A*_{22}\, h_{f,t-1} + \sum_{j=1}^{q} B*_{22}\, \varepsilon_{f,t-1}^{2}$$

$$Q_t = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} = (1 - A - B)\begin{bmatrix} r_s & r_{sf} \\ r_{sf} & r_f \end{bmatrix} + A\begin{bmatrix} \varepsilon_s^2 & \varepsilon_s\varepsilon_f \\ \varepsilon_s\varepsilon_f & \varepsilon_f^2 \end{bmatrix} + B\begin{bmatrix} 1 & \rho_{t-1} \\ \rho_{t-1} & 1 \end{bmatrix}$$

Table 5.4 presents the three mean specifications of the BEKK model, Constant Correlation model and Dynamic Conditional Correlation. The maximum likelihood results are categorized according to the three mean models including Intercept, VAR and VECM specification,[18] respectively.

[18] The number of lags in VAR and VECM models are determined by lag length criteria procedure.

5.2.1.1 Mean specification Results

Based on the mean specification results, the intercept mean model does not provide a good model in posturing both CPO and FCPO returns in all three variance-covariance specification models. Additionally, the VAR models detect significant evidence of both tested returns depending on its own and its counterpart lagged term. The movement of the CPO return tends to be driven by its own lagged terms (1 to 3 lagged terms for the BEKK model and CCC model but 1 to 5 lagged terms for the DCC model) and FCPO lagged terms (1 to 4 lagged term for BEKK model and 1 to 6 lagged terms for the other two models). However, the FCPO returns movement was determined by CPO and FCPO returns lagged terms.[19]The CPO and FCPO returns are likely to have an inverse movement with their own lagged terms but not with their counterparts.

The Johensen cointegration test result exhibited the existence of a cointegration relationship between both series. Therefore, the VECM mean specification was employed and the significance of both error terms confirmed that both series are highly cointegrated in the long-run. The results are consistent with the existing literature for when series are stationary at I(1);the series will possibly cointegrate in the long-term (Kroner and Sultan, 1993; Gagnon and Lypny, 1995; Wilkinson, Rose and Young, 1999;Floros and Vougas, 2004; and Azizan *et al.*, 2007). In contrast, however, Bailie and Myers (1991) found no evidence of cointegration in beef, corn, cotton, gold and soybean prices.

[19] 1 to 6 lagged terms

5.2.1.2 Variance and Covariance Specification Result

The Intercept-BEKK has shown the presence of a significant opposite relationship in the CPO variances with its previous volatility shocks (refer to *G parameters*) and its own shocks (refer to *A parameters*). Meanwhile, the FCPO variance was influenced by the movement of its own previous volatility but no evidence of its squared residual terms. The Intercept-BEKK and VAR-BEKK model reported greater inverse coefficients in both series volatility shocks compared to the effect of its squared residuals. This result infers that the volatility of both series was highly influenced by its previous volatility movement rather than its own shocks. Meanwhile, the VECM-BEKK model exhibited contrary results for the FCPO volatility modelling (Intercept and VAR-BEKK). Additionally, the VECM-BEKK model has proven that there is no evidence to confirm that current CPO volatility is affected by its own volatility shocks.

The covariance results have established a positive significant movement with its previous covariance in the VECM-BEKK model. However, the results are mixed in the VAR-BEKK and Intercept-BEKK models, where the covariance is either positively or negatively affected by its previous series covariance. The covariance estimation results conclude that the series covariance was highly affected by its own lagged covariance term. Subsequently, the previous term for both CPO and FCPO residuals did not assert any influence on the movement of the covariance.

The Constant Correlation and Dynamic Conditional Correlation model exhibit strong evidence that CPO and FCPO volatility are determined by their own volatility shock (refers to *A parameters*) in all three mean specification models. Much higher coefficients were found in the FCPO compared to the CPO volatility clustering model. Such results lead one to conclude that the FCPO returns tend to be influenced by their own shocks (refer to *B parameters*) in a higher parallel magnitude than the CPO return volatility. Both series squared residuals demonstrated a positive relationship that may significantly influence the movement of both CPO and FCPO volatility for all three mean models in the CCC and DCC models. However, there is no evidence to infer the possibility that the FCPO squared residual effects the volatility of the current FCPO returns in the Intercept-CCC model. The DCC model supports the evidence that the correlation between CPO and FCPO is affected by both residual terms and its previous period correlation.

In summary, both the VAR and VECM model appear to provide a good representation model in posturing the CPO and FCPO return. As for BEKK variance clustering models, the CPO variance is likely to be influenced by its own volatility shocks but at a higher magnitude than its own squared residuals (in the VAR and VECM mean model). Consistent results for the BEKK, CCC and DCC models support the evidence that FCPO variance tends to be driven more by its own volatility shocks than its own squared residual for all three mean models. However, the negative coefficient in variance and residuals simply means that a negative shock in the FCPO and CPO returns will increase both market returns volatility or *vice versa*. While, a positive coefficient for FCPO own volatility shock in the VECM-BEKK model describes a positive movement in its own past variance, which will lead to an increase of FCPO market returns volatility. Similar results were demonstrated in the FCPO variance movement, which were reported in all three mean models for the CCC and DCC models. However, the results failed to prove the existence of a relationship between the FCPO squared residuals with the FCPO variance in the Intercept-BEKK and Intercept-CCC models. Nevertheless, the covariance outlined by the BEKK model was more influenced by its own covariance past movement than between the residuals for CPO and FCPO (insignificant H_{sf} in three mean models). Based on the above coefficient estimation results, we can draw a conclusion – there is a strong persistency in volatility in the Malaysian CPO and FCPO markets.

The residual and squared residual diagnostic results for all three mean models for BEKK, CCC and DCC models are shown in Appendixes C, D and E. The Q statistic for both residuals and squared residuals are presented using the 1, 4 and 10 order serial correlations. There was evidence of serial correlation in all Intercept mean models for the BEKK, CCC and DCC models that presence in the CPO and FCPO residual series. However, the same mean models are able to account the minor presence of the autoregressive and heteroscedasticity problem in the CPO and FCPO standardized residuals. The Intercept-CCC model was able to tackle the ARCH problem where the results infer no evidence of ARCH effect for either the CPO or FCPO squared residuals. Furthermore, the Intercept-BEKK and Intercept-DCC were able to support the absence of ARCH effect in FCPO squared residuals in lagged 1 and lagged 10 for Intercept-DCC only.

All three VAR mean models gave a better performance in addressing the serial correlation presence in the CPO and FCPO residuals. Only a minor serial correlation was detected in the VAR-DCC FCPO residual at lagged 4. Further, the findings exhibited an average ARCH effect in all three VAR models. The results support the presence of the ARCH effect in VAR-BEKKCPO residuals at a higher lagged order. However, an identical conclusion was found in lagged 4 and 10 for the VAR-CCC squared residuals series. Only a minor ARCH problem was found in the lagged 10 VAR-DCC FCPO squared residual. Overall, the VAR-BEKK tends to be the most successful model to overcome both the serial correlation and ARCH effect that is present in the FCPO residual series. Meanwhile, the VAR-DCC model appears to be the best as it fully addressed both problems that presence in the CPO residual series.

The VECM mean model for BEKK, CCC and DCC models partly overcomes the serial correlation and ARCH problem in residuals and squared residuals in the tested series. There is no evidence of serial correlation for VECM-BEKKCPO and FCPO series at lagged 4 and lagged 1 for the other two variance models. The VECM-BEKK outperform other models as no ARCH evidence was found in the CPO squared residuals. The results further suggest that the ARCH effect still exists in the FCPO squared residual at lagged 10 for all VECM mean models. However, the CPO squared residuals at order 1 portrayed the non-absence of ARCH problems in the CCC and DCC models. In ARCH effect results, the CCC and DCC gave consistent results for the VECM mean models.

In conclusion, the VAR-BEKK and VAR-DCC appear to provide the best model for CPO and FCPO, respectively, for solving the serial correlation and ARCH issues that are present in both residual series. Yang and Allen (2004) have reported that the VECM-DVECH model failed to encounter the ARCH effect but usefully solved the serial correlation in the residual. They recommended a more dynamic GARCH model to counter these ARCH effects in the squared residual. Based on our results, all three VECM models are considered to be equal second best as they are able to tackle both residual serial correlation and ARCH effect albeit marginally. Finally, compared to the other models, the Intercept model appears to be the worst.

5.2.2 Hedging Performance

5.2.2.1 Minimum variance results (Risk reduction)

Table 5.5: Hedging Ratio estimation results within minimum variance framework

	BEKK			CCC			DCC		
	Intercept(1)	VAR(2)	VECM(3)	Intercept(4)	VAR(5)	VECM(6)	Intercept(7)	VAR(8)	VECM(9)
	In-sample								
No Of Days Forecast									
1 Day	0.21	0.17	0.17	0.84	0.65	0.67	0.6	0.58	0.59
5 Days	0.76	0.24	0.29	0.36	0.54	0.54	0.4	0.39	0.43
10 Days	0.32	0.4	0.38	1.84	0.54	0.55	0.46	0.45	0.5
15 Days	0.74	0.42	0.42	0.17	0.5	0.51	0.46	0.54	0.55
20 Days	1.43	0.64	0.65	0.7	0.51	0.51	0.58	0.56	0.53
	Out-sample								
No Of Days Forecast									
1 Day	0.38	0.61	0.47	0.84	0.65	0.67	0.59	0.57	0.58
5 Days	0.48	0.53	0.53	0.3	0.47	0.48	0.4	0.39	0.43
10 Days	0.48	0.53	0.54	2.08	0.47	0.5	0.45	0.44	0.49
15 Days	0.5	0.48	0.49	0.16	0.49	0.51	0.46	0.55	0.57
20 Days	0.61	0.49	0.49	0.71	0.46	0.46	0.58	0.56	0.54

Note: The hedging ratio is calculated based on $h_t|\Omega_{t-1} = cov_{sf}|\Omega_{t-1}/\sigma_f^2|\Omega_{t-1.}$

Table 5.5 reports the hedging performances through the percentage of risk reduction achieved by all three mean models for the BEKK, CCC and DCC models. The tables are segregated according to out-sample and in-sample data for each model. The results include each 1, 5, 10, 15 and 20 days forecasted period ahead, which are categorized according to the three mean models. The Intercept model has postulated a wider range of hedging ratio within 0.21 to 1.43 (refer to Column 1) compared to the out of sample ratio, which is from 0.38 to 0.61 (refer to Column 1). However, a stable estimation was postured by both VECM-BEKK and VAR-BEKK models within the out-sample data, between 0.48 to 0.61 (refer to Column 2 and 3). In addition, the Intercept-BEKK demonstrates that a higher time horizon will lead to a higher hedging ratio estimation. Subsequently, a contrasting finding was reported in the VAR-BEKK models, which portrayed an inverse relationship between the hedging ratio and forecasting period ahead. However, within the in-sample period, VAR and VECM-BEKK exhibit a similar finding generated in the Intercept-BEKK model. The evidence supports a positive movement between the hedging ratio and the percentage of risk reduction where the lower the ratio, the risk reduction tends to be low and vice versa.

The hedging ratio estimation from the CCC model exhibited a larger range between 0.17 to 1.84 (in Column 4) for the in-sample Intercept-CCC model and 0.16 to 2.08 (in Column 4) for the same out-sample forecasted period. This evidence indicates that within the in-sample analysis, the CPO market participant tends to hedge from the range of 17% to 184% of its spot position and 16% to 208% of its spot position within the out-sample results. The highest ratio was generated from the 10-day forecasting period, which was 2.08 for the out-sample and 1.84 for the in-sample Intercept model. However, a consistent range of hedging ratio was reported for both the VAR and VECM-CCC models for both the in-sample and out-sample data (between 0.46 to 0.67 – Column 5 and 6). Similarly, the VAR-BEKK, VAR and VECM-CCC models support the evidence that a lesser time horizon tends to give a higher hedging ratio. However, the risk reduction findings gave a monotonic hedging performance at any forecasted period. In the theoretical framework chapter, the risk reduction measurement similarly refers to the squared correlation between the FCPO and CPO returns. Therefore, the constant risk reduction estimated in the CCC model is not surprising since the model conjectures a constant correlation between both series.

In contrast to the CCC model, the DCC model assumes a dynamic process for series correlation. Within the three variance models, the DCC model estimated the most similar hedging ratio results either in the in-sample or out-sample analysis. The model estimated that between 39% and 60% spot proportion (refer to Column 7, 8 and 9) needs to be hedged and that these proportions or ratios shared the same cycle throughout the multiple forecasting horizons. In addition, the longer the period forecasted ahead, the higher the risk reduction can be achieved either in the in-sample or out-sample estimation results. Overall, the above evidence tends to support that the time factor exists in hedging ratio estimation and contests the static hedging ratio.

Table 5.6: Hedging performance results within minimum variance framework

	BEKK			CCC			DCC		
	Intercept	VAR	VECM	Intercept	VAR	VECM	Intercept	VAR	VECM
				Insample					
No Of Days Forecast									
1 Day	6.81%	4.70%	4.31%	28.53%	35.66%	36.81%	30.69%	27.63%	27.42%
5 Days	44.36%	7.45%	9.80%	28.53%	35.66%	36.81%	30.60%	26.22%	31.53%
10 Days	18.06%	26.35%	22.92%	28.53%	35.66%	36.81%	31.01%	34.02%	38.02%
15 Days	65.84%	31.80%	30.95%	28.53%	35.66%	36.81%	32.06%	43.91%	44.88%
20 Days	69.81%	43.24%	46.08%	28.53%	35.66%	36.81%	42.05%	54.99%	54.22%
				Outsample					
No Of Days Forecast									
1 Day	27.30%	40.21%	18.81%	29.37%	36.66%	37.86%	29.69%	26.45%	26.10%
5 Days	32.88%	35.94%	40.57%	29.37%	36.66%	37.86%	30.47%	25.52%	29.71%
10 Days	30.46%	38.93%	35.81%	29.37%	36.66%	37.86%	30.57%	33.13%	36.89%
15 Days	34.65%	34.19%	45.94%	29.37%	36.66%	37.86%	31.87%	45.49%	46.94%
20 Days	68.68%	32.77%	45.36%	29.37%	36.66%	37.86%	42.79%	55.69%	55.66%

Notes
The variance of unhedged portfolio is generated from the variance of CPO (Var (UnHE) = σ_s^2).
The variance of Hedged portfolio is computed based on Var (HE) = $\sigma_s^2 + h^2 \sigma_f^2 - 2 h \sigma_{sf}$.
The hedging effectiveness or risk reduction is calculated based on *HE = [1 – Var(HE)*/Var (UnHE)]* = ρ^2.

Table 5.6 describes the risk reduction achieved by the hedger. It is segregated into 1, 5, 10, 15 and 20 days forecasting period ahead for all the tested models.[20] The hedging performance results show that the Intercept-BEKK model is likely to give the highest variance reduction of 60% for in-sample data (15 and 20 days forecasting period) and out-sample data (20 days forecasting period). However, the Intercept-BEKK model gives the worst performance for the 1 day forecasted period. During that day, the hedgers were only able to minimize 4% from their total price risk exposure

[20] Please refer to Appendices F, G and H for the detailed results for minimum variance measurement.

(within the in-sample period). More similarity with the hedging performance was found in both the CCC and DCC models for the in-sample and out-sample period. An average range of 30% to 38% variance reduction was achieved in the CCC estimation while DCC indicates that an average of 26% to 55.6% of variance reduction can be attained in all three mean models (in all forecasted horizon). Although both the CCC and DCC models have portrayed a consistent risk reduction the magnitude is modest. In addition, the BEKK model (especially in its Intercept model) tends to have a wider ranger of risk reduction, between 4% and 66%. The BEKK model demonstrates the same movement between the forecasted period ahead and its risk reduction; a higher forecasted horizon will give a better risk reduction result.

In conclusion, there is no definite answer as to which model is considered best in terms of the risk reduction achieved in hedging portfolio against the non-hedging position. Although the evidence is mixed, based on the findings, the BEKK-Intercept tends to outcast the other models for the 5, 15 and 20 period for in-sample and the 20 forecasting period for out-sample estimation.[21] These results do not fully support that the VECM mean model is superior in terms of variance comparison to all the dynamic models, similar to Kroner and Sultan (1993), Yang and Allen (2004) and Ford, Pok and Poshakwale (2005). However, it is in contrast to Lien, Tse and Tsui (2002) where the CCC model tends to be less superior albeit they compared the hedging performance to

[21] Similar evidence reported in:
Lee and Yoder (2007) – the outstanding performance from the BEKK model.
Baillie and Myers (1991), Bera et al. (1997), Haigh and Holt (2002), Kumar et al. (2008) – the dynamic model gives better performance than the static model.

the static model (not to other dynamic models). In the hedging ratio context, Lien (2004) concludes that the exclusion of error term (ECM) in means specification estimates a lesser hedging ratio. Obviously, the above findings do not support Lien (2004), since the VECM models, generally, do not estimate the highest hedging ratio as compared to the Intercept and VAR mean models. For example, the Intercept mean model of the BEKK, CCC and DCC models provides a higher hedging ratio than the VECM mean models. Further, Wilkinson, Rose and Young (1999), and Floros and Vougas (2004) document evidence that the EC model was not the best model to estimate higher hedging ratio than the OLS model.

5.2.2.2 Utility maximization Function

Table 5.7: Hedging Performance in the Utility Maximization Function
for the BEKK model

Φ	**Intercept-BEKK**	**VAR-BEKK**	**VECM-BEKK**
		In-sample Comparison	
0.5	-0.4264343	-0.9590828	-1.1011248
1	-0.6764343	-1.2090828	-1.3511248
1.5	-1.4264343	-1.9590828	-2.1011248
2	-2.9264343	-3.4590828	-3.6011248
2.5	-5.4264343	-5.9590828	-6.1011248
3	-9.1764343	-9.7090828	-9.8511248

	Out-sample Comparison		
0.5	-0.1000179	-0.747267	-0.7490781
1	-0.3500179	-0.997267	-0.9990781
1.5	-1.1000179	-1.747267	-1.7490781
2	-2.6000179	-3.247267	-3.2490781
2.5	-5.1000179	-5.747267	-5.7490781
3	-8.8500179	-9.497267	-9.4990781

Note:
Utility Maximization function for hedging portfolio and unhedged portfolio are computed based on 20 days forecasting period ahead. The utility quadratic function is generated from equation 56 and the **Φ** denotes the degree of risk aversion for investors ranging from 0.5 to 3.0.

Table 5.8: Hedging Performance in the Utility Maximization Function for the CCC model

Φ	**Intercept-CCOOR**	**VAR-CCOOR**	**VECM-CCOOR**
	In-sample Comparison		
0.5	-0.7344753	-0.8802515	-0.9354166
1	-0.9844753	-1.1302515	-1.1854166
1.5	-1.7344753	-1.8802515	-1.9354166
2	-3.2344753	-3.3802515	-3.4354166
2.5	-5.7344753	-5.8802515	-5.9354166
3	-9.4844753	-9.6302515	-9.6854166

Out-sample Comparison			
0.5	-0.7695699	-0.9449881	-0.9811746
1	-1.0195699	-1.1949881	-1.2311746
1.5	-1.7695699	-1.9449881	-1.9811746
2	-3.2695699	-3.4449881	-3.4811746
2.5	-5.7695699	-5.9449881	-5.9811746
3	-9.5195699	-9.6949881	-9.7311746

Note:
Utility Maximization function for hedging portfolio and unhedged portfolio are computed based on 20 days forecasting period ahead. The utility quadratic function is generated from equation 56 and the **Φ** denotes the degree of risk aversion for investors ranging from 0.5 to 3.0.

Table 5.9: Hedging Performance in the Utility Maximization Function

for the DCC model

Φ	**Intercept-DCC**	**VAR-DCC**	**VECM-DCC**
In-sample Comparison			
0.5	-0.5074428	-0.7854597	-0.9318357
1	-0.7574428	-1.0354597	-1.1818357
1.5	-1.5074428	-1.7854597	-1.9318357
2	-3.0074428	-3.2854597	-3.4318357
2.5	-5.5074428	-5.7854597	-5.9318357
3	-9.2574428	-9.5354597	-9.6818357

Out-sample Comparison			
0.5	-0.49599	-0.8729597	-0.8948126
1	-0.74599	-1.1229597	-1.1448126
1.5	-1.49599	-1.8729597	-1.8948126
2	-2.99599	-3.3729597	-3.3948126
2.5	-5.49599	-5.8729597	-5.8948126
3	-9.24599	-9.6229597	-9.6448126

Note:
Utility Maximization function for hedging portfolio and unhedged portfolio are computed based on 20 days forecasting period ahead. The utility quadratic function is generated from equation 56 and the Φ denotes the degree of risk aversion for investors ranging from 0.5 to 3.0.

Thus far, the previous section discussed the performance of hedging strategy using the minimum variance framework; this section expands the hedging performance in the utility maximization framework in various dynamic models. The results for all the estimation models are presented in Tables 5.7, 5.8 and 5.9, respectively. The framework measures the performance of such strategy considering mean return, risk aversion and variance attained in the hedging strategy (refer to equation 9). Previous evidence has compared the static and the non-static model and inferred that the largest utility maximization is achieved by the non-static model (Kroner and Sultan, 1993; Gagnon and Lypny, 1995; and Yang and Allen, 2004). However, this research was more focused on comparing the utility maximization among the dynamic models (BEKK, CCC and DCC model).

All three tables (refer to Tables 5.7, 5.8 and 5.9) outline the hedging performance in the utility maximization function within 0.5 to 3.0 risk aversion level within the in-sample and out-sample for 20 days ahead forecasting period. The results support that the Intercept model outperforms in both in-sample and out-sample data for all three GARCH models. However, overall, the Intercept–BEKK model gives the largest utility maximization within the in-sample and out-sample period. In contrast, the VECM model exhibits the worst hedgers utility maximization performance among all tested models. The results further support that the higher level of hedger's aversion, the less the utility maximization function is achieved. In addition, empirical evidence supports a lower mean return posture in the dynamic models compared to the static models (Yang and Allen, 2004). Intuitively, when investors have a higher risk aversion it portrays a lesser tolerance towards the additional risk exposed by them. Further, a higher level of risk aversion (Φ) will lead to a larger variance $\{1/2\phi VAR(RH_t|\Omega_{t-1})\}$. Ultimately, the imbalance between the mean return and the variance will result in a larger negative utility maximization achieved by hedgers, especially when the return portion $\{E(RH_t|\Omega_{t-1})\}$ is small.

5.2.3 Conclusion

Initially, the research investigated whether various mean specifications have a significant effect on the hedging effectiveness in the Malaysian Crude Palm Oil markets. The study focuses on the Intercept, VAR and VECM mean modelling for the BEKK, Constant Correlation model and Dynamic Conditional Correlation model (refers to nine models). Apart from an evaluation of common multi-variance specification models, our research attempts to prove the importance of various mean specifications that may give different hedging performance results.

The diagnostic test results provide the existence of non-normality features in both the CPO and FCPO series. Serial correlation and autoregressive and heteroscedasticity problems were established in both residuals and squared residuals, respectively. Therefore, dynamic models are more appropriate to model the time varying second moment of the CPO spot and futures returns. Both the VAR-BEKK and VAR-DCC were found to fit with the CPO and FCPO, respectively. The models were able to counter both the serial correlation and ARCH effect that were present in both the residual and squared residual series, however, in the VECM models it is likely to partly overcome the issues. It is not surprising that the Intercept models were acknowledged to be the least satisfactory among all the models in overcoming the serial correlation and ARCH issues, since the means were only ran against its intercept. Therefore, it is understandable that this intercept model has a less satisfactory result than the other models.

In respect of the hedging ratios estimations results, the estimation proved that the hedging ratio tends to be in a non-monotonic process, which is consistent with prior empirical evidence. Additionally, the variance reduction results were mixed and the Intercept-BEKK models appear to be the best in all BEKK, CCC and DCC models within the in-sample forecasted periods (20 days). Meanwhile, within the out-sample analysis, similar results were reported for the BEKK and DCC models. However, the CCC model has proven that the VAR model outperforms the other mean models. In addition, when the utility maximization function is considered, the Intercept-BEKK and VECM-BEKK models tend to be superior for the in-sample and out-sample periods. It was also revealed that when hedgers are willing to tolerate a risky position, it will elevate the hedger's utility level. Overall, the findings acknowledge that the error term mean specification may influence the degree of risk minimization, however, the magnitude is merely low. Nevertheless, interestingly, the intercept model turned out to be superior when judged against the investor's utility maximization function. The conclusion is intuitively appealing where different mean and variance specification models tend to affect both the degree of risk minimization and the hedgers utility maximization, albeit marginally. Additionally, the evidence supports the superior performance of the Intercept-BEKK models, which gave the best hedging performance measurement results.

SECTION III

5.3 EFFECT OF STRUCTURAL BREAKS ON VOLATILITY CLUSTERING BEHAVIOUR AND HEDGING PERFORMANCE ESTIMATION

Modelling the structural breaks has taken the centre stage in empirical macroeconomics and finance. This is evident from the ever-increasing number of publications that have discussed this issue in recent decades. The implications of failing to account for structural breaks in econometric modelling are many. Two of the well-known implications are: (1) the tendencies to erroneously support that the time series behave as a non stationary process rather than a stationary process in the preliminary unit-root diagnostic test (Zivot and Andrew, 1992) and (2) a misspecified model, which could lead to an error in estimation and forecasts.

Bai and Perron (1998) developed a comprehensive test that allows for multiple break identification, which may exist in series means. The notion of a structural break is not strictly restricted to the mean specification of a series. In fact, more recently, the regime shift identification has extended into the series second moment specification (see Inclan and Tiao, 1994). They introduced a similar test based on the Iterated Cumulative Sums of Squares [ICSS] algorithm but catered for a series variance. These procedures have been applied to many macroeconomic variables such as exchange rate (Rapach and Strauss, 2008), US interest rate (Bai and Perron, 2003), growth national product (Fang, Miller and Lee, 2008) and in the securities markets (Aggrawal, Inclan and Leal, 1999). By and large, the empirical evidence points to the importance of identifying and modelling these breaks in both the mean and volatility specifications in order to generate correct estimates of the model and its forecasts. On that basis, it is rudimentary to check for the existence of structural breaks in the series and to account for them in the modelling exercise.

In the hedging context, practically, the hedging decision is likely to change over time. By definition, the hedging decision synonymy refers to the hedging ratio that shows the proportion of the futures contractsagainst the spot market. Also, the hedging decision is believed to be in a non-monotonic fashion since hedgers sometimes enter into the market to hedge less and sometimes more (Karp, 1987). Empirical evidence confirms the rationality of the non-monotonic characteristic of hedgers decisions because they then change the hedging percentage in consideration of the information available in the market. Fung *et al.* (2006) infer that fund managers tend to have a non-static hedging decision. They tend to change their hedging strategies to correspond to their risk factor concerning the environmental changes. A similar result was found in Meligkotsidou and Vrontos (2008). The source of environmental changes can be demarcated within the internal context (local aspect) and the external context (refers to the international aspect). Empirically, many researchers have determined the presence of a regime shift in various macroeconomic series and while most concentrate on the international context (see Fang, Miller and Lee, 2008; Fang and Miller, 2008; Rapach and Strauss, 2008; Andreou and Ghysels, 2002) some combine these two aspects (refer to Aggrawal, Inclan and Leal, 1999 and Zhang, Jeffrey and Rusell, 2001). However, very few studies have explored the significance of structural breaks within spot and futures prices.

In addition, Lien (2005) specifies three elements that may potentially make the hedging ratio estimation less accurate:i) a smaller sample size (in estimation and test sample), which makes the estimation of hedging ratio less accurate and, further, will fail to prove the effectiveness of hedging correctly;ii) the presence of a regime shift in the tested series and, finally, iii) inconsistent criterion specified in the estimated and tested sample. His paper conceptually proved that the ECM model is able to outperform the OLS model when a structural break is considered in the estimation model. Lien further highlights the omission of a structural break that may spuriously estimate the hedging ratio and, therefore, we believe that the hedging performance estimations will also be affected. However, limited research investigates the implications of structural breaks in the spot and futures return on hedging decisions and its performance (see Lee and Yoder, 2007). They suggest that a regime shift is an important element that may give a superior result for the ECM estimation model compared to the conventional model. Based on this evidence, we can safely assume that a regime shift may influence the hedging performance result.

As such, this research attempts to investigate the effect of a structural break on the hedging decision process within the BEKK estimation model in the crude palm oil market.[22] To identify the structural break number and dates, the study applies the Bai and Perron (1998, 2004) procedure for mean, with both the Inclan and Tiao (1994) and the Modified ICSS procedure (Sanso *et al.*, 2004) for series variance. Further, the research will postulate the seriousness of the non-inclusion of the structural break in hedging performance analysis vis-à-vis the structural break model. The research will consider both the minimum variance and the utility function measurement for hedging performance analysis.

This research extends the existing literature in a number of ways. First, it complements previous research on the issue of structural breaks with applications on financial and macroeconomic series from developed markets, by considering the application of structural break tests on commodity returns series from an emerging market. Second, there has been considerable investigation of the issue of structural changes in macroeconomic variables while very little attention has been given to agricultural commodity returns. As the agricultural sector is intertwined with other sectors and constitutes a major contribution to economic activity, economy-wide changes in the levels of economic activity would have a direct impact on the agricultural sector. Furthermore, concerning changes in the economic structure, agriculture is perhaps more prone to shocks caused by weather, which can have sustained and lasting effects. In addition, technological changes can alter productivity levels and can shift the way resources are allocated, thus, having a permanent effect on the agricultural sector. Moreover, major policy reforms, both at the national and

[22] Refer to the third objective of this study in chapter 1. The BEKK intercept model was selected in this structural break investigation since the model appears to be superior in both hedging performance results presented in Section II (**DIVERSE MEAN AND VARIANCE SPECIFICATIONS versus HEDGING PERFORMANCES**)- pg 133-134.

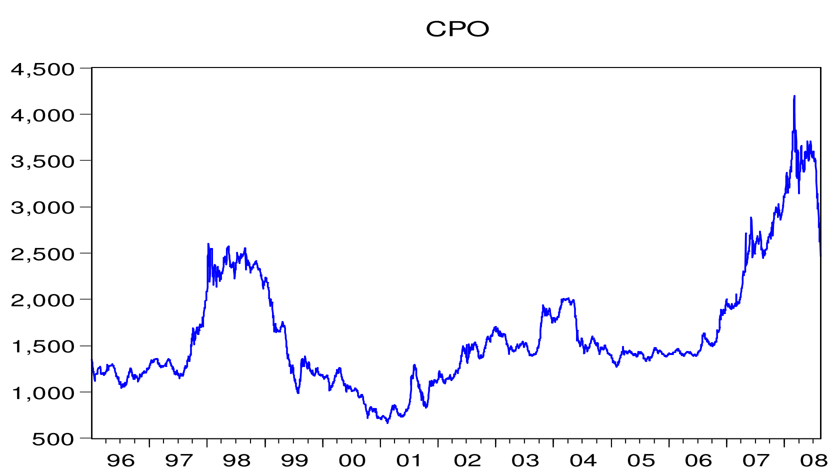
international levels, can induce some structural changes in prices. Third, identification of breaks in the mean and variance of the returns series, as well as in the cointegrating relationship between the spot and future returns suggests that these breaks need to be incorporated in the model specification to provide more precise persistency inference. The research attempts to associate the structural break effect on the hedging performance estimation result. Ultimately, we analyse the consistency of hedging performance achieved across the tested period.

5.3.1 Time Series Volatility Analysis

Figure 5.1: Plot for CPO and FCPO prices

Figure 5.1 (a): Plot for CPO prices

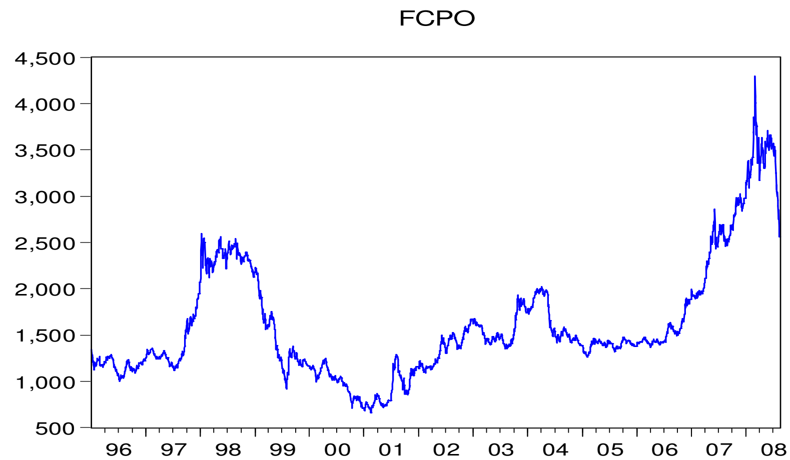
(RM)



Year

Figure 5.1 (b) FCPO prices

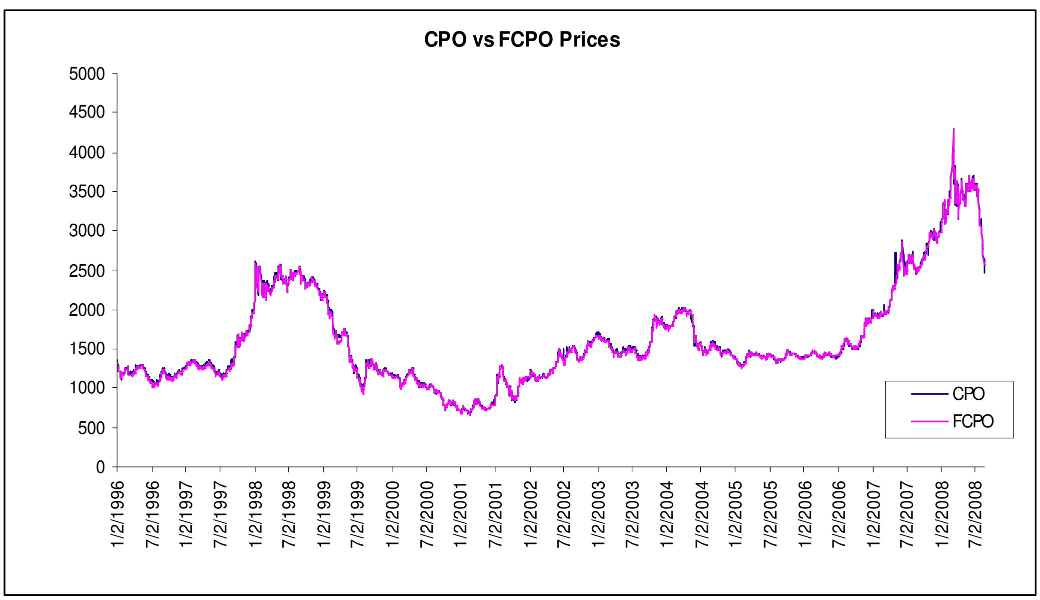
(RM)



Year

Figure 5.1 (c): Plots for CPO vs FCPO Prices

(RM)

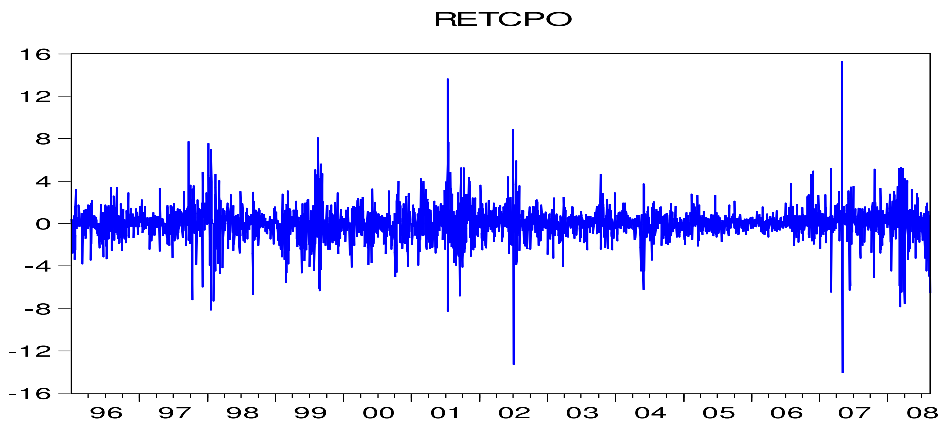


Year

Figure 5.2: Plot for CPO and FCPO returns

Figure 5.2 (a): Plot for CPO returns

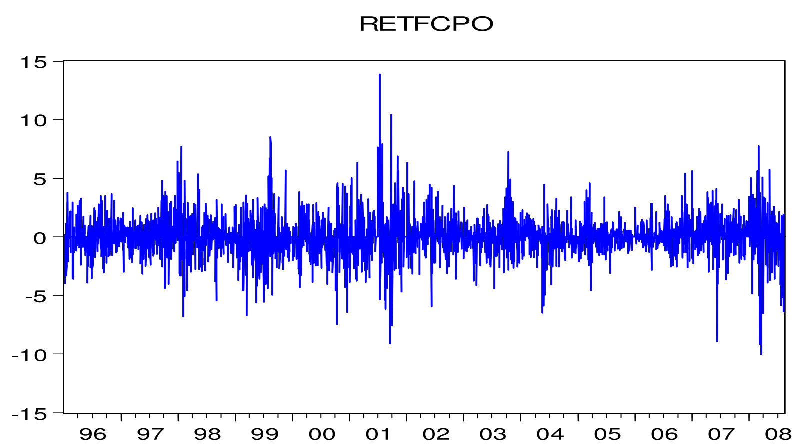
(%)



Year

Figure 5.2 (b): Plot for FCPO returns

(%)



Year

The structural break effect analysis begins with the basic plotting of tested series prices and returns throughout the sampling period. Figure 5.1 presents both the CPO and FCPO prices for the period between January 1996 and August 2008. These series tend to establish a homogeneous pattern, and we can assume that these series are likely to move together (see Figure 5.1 (c)). During the Asian Financial Crisis, crude palm oil prices recorded a steep hike from RM1,300 per metric tonne in mid 1997 to RM2,500 per metric tonne in early 1998. During the same period, the CPO production increased due to a good biological yield cycle during that particular year. Later, a tranquil movement in CPO and FCPO prices was registered after the Asian financial crisis, from 1999 up unto 2006. Another dramatic price movement was exhibited in early 2007 and thereafter the CPO price reached its peak at almost RM4,000 per metric tonne in early 2008. In spite of the global recession starting in early 2007, these prices were pushed up by a slower CPO production. The short supply was due to the weather conditions that affected the level of CPO production during that specific period. Furthermore, the lower production was also due to the seasonal downcycle during that year. The supply shortage continued into 2008, supported by the robust global demand for such commodities, boosting the price to the highest amount during that period.

Referring to volatility plotting in Figure 5.2, the CPO returns experienced the most turbulent period in 2001 and again in 2007. However, in 2007 a less volatile movement was reported for FCPO returns. A more uncertain movement was continuously exhibited in FCPO from 1997 up to its peak in year 2001. During the

Asian financial crisis, both series experienced a highly volatile pattern, similarly, during the current global recession and commodity production pressure.

Based on the above evidence, we can conclude that both series, prices or returns, presented certain regime changes throughout 1999 to 2008. These changes were contributed from the local and external factors that directly or indirectly affect those series movements. The CPO prices and returns volatility were more affected by the sudden market condition from the United States than its own surrounding turbulence (such as the Asian Financial Crisis). For internal factors, the supply or production forces play a critical role in making this vegetable oil's price and returns more variable. While the demand function is less likely to make the returns more uncertain because of the strong consistent global demand for the vegetable oil. The current jump in crude oil prices made many countries search for an alternative source of energy such as biofuels and spurred the CPO demand curve. In addition, the CPO is also largely used in the food processing industry, especially in China and India, which strengthened the CPO demand over time.

5.3.2 Structural Break Test Results

Referring to the CPO and FCPO plotting price and return series in the previous section, we can generally expect some regime shift throughout the sampling period. However, we do not know the exact date and number of regime shifts within the sampling period. Since the literature has proven the importance of detecting the correct number of breaks in capturing more precise volatility estimation, as such, we further proceed to perform the three break identification procedures within for mean, variance and cointegration context.

5.3.2.1 Structural Breaks in Variance

The study adopted the IT ICSS and adjusted ICSS (k_1 and k_2) tests and the results are presented in Appendix I. The IT ICSS results identified 41 breaks present in the CPO variance, while only 12 breaks were confirmed by the k_1 ICSS test results. The similar variance break dates detected by both the IT and k1 ICSS tests were 14/04/1997, 19/09/1997, 02/01/1998, 10/03/1998, 08/09/1999, 01/10/2001, 05/08/2002, 25/03/2005 and 24/10/2005. In addition, the k_1 test identified additional breaks 07/10/1996, 10/05/1999 and 02/08/1999. However, no structural breaks were reported under the k_2 test.

By referring to the FCPO, the IT ICSS proved fewer breaks than posited in the CPO variance while similar break numbers were shown in the k_1 test. There were 22 breaks for IT ICSS and 11 breaks in the variance series. However, only four breaks were recognized by the k_2 test. All three tests have one similar structural date, which was 31/10/1996. In addition, both the IT and k_1 consistently identified breaks on 31/10/1996, 20/10/1997, 26/12/1997, 12/02/1998, 08/09/1998, 01/04/2005, and 31/03/2006. However, the k_1 further identified new structural changes in variance present on 02/07/2001 and 11/01/2008. Finally, one new structural change was detected from k_2's four breaks, which was located on 18/03/2008.

Based on the findings, obviously most of the breaks occurred during the Asian Financial Crisis (within 1997 and 1998) and post Asian Financial Crisis in 1999 where the Malaysian government placed a capital control and pegged the Malaysian Ringgit against the US Dollar. Locally, the volatility during this period might be contributed from a generous growth in production that was due to a good biological cycle for the commodity. Another break was registered in October 2001, a few weeks after the terrorist attacks in the US. However, the structural change in the variance CPO return is not directly hurt by this event. The attack had an almost instantaneous affect on the US stock markets and contagiously towards the global stock markets volatility. This series variance changes tend to be influenced by domestic forces, which consist of CPO production shortage (lower biological cycle) and more markets towards the stock markets movement. In addition, the intense competition with other vegetable oil (soy oil, rapeseed oil and sunflower oil) producers who increased their production may have made the CPO market more volatile that year.

The lower production continued to be experienced in 2002, partly due to the low biological cycle of the CPO trees, and the unstable weather, which might have contributed to the supply shortage. These factors further pressured the CPO markets and explicitly translated into volatility in CPO returns. The oil price shocks in 2005 and 2006 further benefited the CPO producers. The popularity of the biofuel as another energy option increased the world CPO demand curve and pushed the price further. The downward supply in other vegetable oils and fats in 2005 made the CPO prices fluctuate more.

The final structural breaks in CPO variance were identified in March 2008, which were due to the global recession that was triggered by the US Mortgage Sub Prime crisis in early 2007. The global recession caused countries to implement measures to strengthen their liquidity and financial infrastructure. This pressure further translated into a downward trend in the oil and commodity prices, which includes CPO. In addition, the level of CPO production was very encouraging along with the great support from the world demand for such oil during that period. In addition, a weak production by other vegetable oil producers is believed to have further secured the CPO prices. Nevertheless, the current global turmoil has heightened the uncertainty in the movement of CPO prices, which overshadowed the good CPO demand forces.

5.3.2.2 Structural Break in Mean (Bai and Perron Test Results)

Table 5.10: CPO return (3 January 1996 – 15 August 2008)

Specifications						
zt = {1}	q = 1	p = 0	h = 164	M = 5	ε = 0.05	
Tests						
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$	*UDmax*	*WDmax*
3.9760	9.1476**	5.8430	5.8125	6.2259	9.1476*	9.322*
SupF(2|1)	SupF(3|2)	SupF(4|3)	SupF(5|4)			
10.0667*	3.7193	3.2390	2.9660			
Number of Breaks Selected						
Sequential : 0						
LWZ : 0						
BIC : 0						
Structural Breaks Date						
SB 1:	09/11/1998 (744)	SB 2:	28/07/1999 (931)			
Parameter Estimates with Two Breaks						
α	D1	D2	Sub-period 1	Sub-period 2	Sub-period 3	
0.0788	-0.5481	0.5072	0.0788	-0.4693	0.0379	
(0.0549)	(0.1225)***	(0.1137)***	03/01/1996 - 6/11/1998	09/11/1998- 27/07/1999	28/07/1999- 15/08/2008	

The $supF_T$ (k) tests with autocorrelation allowance in its disturbances. Further follow Andrews (1991) and Andrews and Monahan (1992), the covariance matrix with autocorrelation and heteroscedasticity is constructed adopting a quadratic kernel (an automatic bandwidth using AR(1) approximation). While, the errors are pre-whitened using VAR(1).

Notes:
Standard errors are given in the parentheses
*** represents 1 % level of significance
** represents 5 % level of significance
* represents 10 % level of significance

Table 5.11: FCPO return (3 January 1996 – 15 August 2008)

Specifications						
zt = {1}	q = 1	p = 0	h = 164	M = 5	ε = 0.05	
Tests						
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$	*UDmax*	*WDmax*
4.2273	8.8389**	7.5893*	5.8110	6.7800**	8.8389*	9.0074
SupF(2|1)	SupF(3|2)	SupF(4|3)	SupF(5|4)			
9.7387**	3.9313	2.4722	2.4722			
Number of Breaks Selected						
Sequential	:	0				
LWZ	:	0				
BIC	:	0				
Structural Breaks Date						
SB 1:	01/12/1998 (760)	SB 2:	30/07/1999 (933)			
Parameter Estimates with Two Breaks						
α	D1	D2	Sub-period 1	Sub-period 2	Sub-period 3	
0.0711	-0.5962	0.5681	0.0711	-0.5251	0.043	
(0.0586)	(0.1360)***	(0.1272)***	03/01/1996 - 30/11/1998	01/12/1998-29/07/1999	30/07/1999-15/08/2008	

The $supF_T$ (k) tests with autocorrelation allowance in its disturbances. Further follow Andrews(1991) and Andrews and Monahan (1992), the covariance matrix with autocorrelation and heteroscedasticity is constructed adopting a quadratic kernel (an automatic bandwidth using AR(1) approximation). While, the errors are pre-whitened using VAR(1).

Notes:
Standard errors are given in the parentheses.
*** represents 1 % level of significance
** represents 5 % level of significance
* represents 10 % level of significance

Tables 5.10 and 5.11 summarize the BP test results for CPO and FCPO returns, respectively. In Table 5.10, the sup $F_T(1)$ test is virtually insignificant at all three levels of significance. However, a contradictory result was given when we tested at sup $F_T(2)$. The result exhibits two potential structural breaks in the CPO mean at the 5% level of significance. These two breaks were further validated via the sup $F_T(m+1|m)$ test results. This indicates that the sup $F_T(2|1)$ is significant at 10% and similarly suggests the existence of two changes in the mean tested series. In contrast, when referring to sequential procedure, the BIC and LWZ, these three tests unfailingly select no structural break. This is an inevitable result as the earlier sup $F_T(1)$ test is statistically not significant; therefore, these three tests will definitely portray a similar result to sup $F_T(1)$. In sum, the existence of two breaks are strongly supported by the significant results in sup $F_T(2)$, sup $F_T(2|1)$, UD max and WD max tests. Intuitively, we can conclude that two significant structural changes exist in the RCPO mean between January 1996 and August 2008.

Moreover, two structural breaks were located at 09/11/1998 and 28/07/1999. In order to verify the changes of mean that took place during these two break dates, we divide the observation into three sub-periods – 03/01/1996-06/11/1998 (SB 1), 09/11/1998-27/07/1999 (SB 2) and, finally, 28/07/1999-15/08/2008 (SB 3). Next, we included two dummy variables in the mean equation to cater for these two shift periods. Both the dummy coefficients are highly significant and further strengthen the structural shift in mean within these three sub-periods. The mean estimation model indicated a positive mean of 0.0788 and 0.0379 in the first and third sub-period, while a negative mean was reported in the second sub-period (-0.4693).

Empirical evidence infers that the futures market tends to move together with the spot market. With reference to the evidence, we conjectured that there is a tendency in the mean FCPO returns to undergo potential structural changes similar to the CPO returns. In Table 5.11, both the sup $F_T(1)$ and sup $F_T(4)$ exhibited similar insignificance at any 10%, 5% and 1% alpha value. However, when testing sup F_T (k) at 2, 3 and 5, successfully the test highly rejects the null hypothesis of no structural breaks and accepts the existence of 2 and 5 potential structural shifts in FCPO mean returns at the 5% level of significance. The test results also show three breaks at the 10% level of significance. However, when referring to the sup $F_T(m+1|m)$ test, the results validated two structural breaks, but not for the other higher level than the sup$F_T(2|1)$ test results. Meanwhile, a contrary result was reported between UD max and WD max test results, where UD max is positively significant at 10%, but WD max is not significant. Unlike other tests, the sequential procedure, LWZ and BIC were found to establish a similar conclusion to the CPO return. There were no breaks reported under these three procedures. With similar reasons to the CPO return, the non existence of breaks identified was due to the trivial result given in the sup $F_T(1)$.

Summarizing all these related results, the sup $F_T(2)$, sup $F_T(2|1)$ and UD max test supported the presence of two breaks in the FCPO mean return. Hence, we can comfortably accept the existence of two breaks, and proceed to include the two dummy variables, which represent these shifts in the FCPO mean estimation model. The break dates were on 01/12/1998 and 30/07/1999, which were less than a month away from the CPO returns breaks. Similar to CPO, we then demarcated the full sample period into three sub-periods consisting of 03/01/1996-30/11/1998, which represented sub-period 1, 01/12/1998-29/07/1999 for sub-period 2 and 30/07/1999-15/18/2008 for sub-period 3.

Consistent with the CPO return, the evidence indicates the significance of both regime shifts in the FCPO mean estimation model. Moreover, the beta coefficient for dummy 1 was substantially reduced to 0.5962 during the second sub-period. Subsequently, the coefficient increased to 0.5681 for the respective sub-period. In conclusion, these findings infer the significance of two breaks affecting both the CPO and FCPO mean return between January 1996 and August 2008.

In relation to external factors, the breaks occurred within the post Asian financial crisis and, domestically, the CPO market performance was caused by a generous production in such oil during that period *(Source: BNM Annual Report 1997/1998).* Interestingly, the mean shift is much lower than the variance structural breaks occurring in both series. This is logical as both returns volatility are sensitive to external and internal events. The sensitivity may influence the trading reaction of producers and buyers (as hedgers, speculators or arbitragers), which may push the commodity prices either downwards or upwards.

5.3.2.3 Structural Break in Cointegration Relationship (GH-Cointegration Test Results)

Table 5.12: Gregory Hansen Cointegration Test between CPO and FCPO

	t-Stat	**Structural Break**
Test 1:	-6.72794	15/06/2000***
Test 2:	-7.22731	16/05/2002***
Test 3:	-7.11043	15/06/2000***

Note:

Test 1 is the cointegration test with structural break in level, while Test 2 is the test with level changes and trend. Finally Test 3 is the cointegration test, which allows the full structural breaks in mean and slope coefficient.

Critical value for Test 1: 1% -5.13000, 5% -4.61000 and 10% -4.34000
Critical value for Test 2: 1% -5.45000, 5% -4.99000 and 10% -4.72000
Critical value for Test 3: 1% -5.47000, 5% -4.95000 and 10% -4.68000

*** represents 1 % level of significance
** represents 5 % level of significance
* represents 10 % level of significance

Table 5.13: Parameter estimation for Gregory Hansen Cointegration Test between CPO and FCPO

	μ_1	μ_2	α_1	α_2	β_1	β_2
Test 1:	0.01456 (0.00061)***	1.0000 (0.00084)***	-0.0111 (0.0005)***	-	-	-
Test 2:	0.00537 (0.00696)	1.0002 (0.00094)***	0.00332 (0.0021)	-	-0.00001 (7.95-07)***	0.000005 (1.21-06)***
Test 3:	0.1441 (9.41-03)***	0.9825 (1.306-03)***	-0.2551 (0.014)***	0.0360 (2.057-03)***	-3.254-06 (1.172-06)***	-6.4034 (1.43-06)***

Notes:
$\mu 1$ and $\mu 2$ represent Intercept and Intercept dummy.
$\alpha 1$ and $\alpha 2$ represent slope coefficient for RFCPO and Slope coefficient Dummy for RFCPO
$\beta 1$and $\beta 2$ represent trend coefficient and trend coefficient dummy

Standard errors are given in the parentheses
*** represents 1 % level of significance
** represents 5 % level of significance
* represents 10 % level of significance

The two previous subsections discussed the structural breaks experienced in the tested series mean (BP tests) and variance (ICSS tests). Consistent with existing literature, we assumed that both CPO and FCPO series tend to move together and there will be a long run relationship at the series level. As such, we extended the structural break investigation within both series cointegration relationships. The procedure used was the GHcointegration test and Table 5.12 reports the test results. We further used three tests within the GH cointegration procedure, consisting of Test 1, which examined the cointegration test with structural break in level; Test 2 focused on testing the structural break in level changes and trend; and, finally, Test 3, the cointegration test that permitted a full structural break in mean and slope coefficient. The results indicate slightly similar break dates, which were located on 15 June 2000 for both Test 1 and Test 3 (Full Structural Breaks in mean and slope). During the period there was a Technology Bubble, which may have possibly contributed to the regime shift, however, domestically, the CPO production pressure (due to low biological cycle) is believed to have made the market more volatile. The break date shifts to 16 May 2002, when a structural break in level changes and trend model was tested. The regime shift is similarly due to the low supply pressure as during that period Malaysia faced a climate crisis that made the palm trees stress out. All three tests consistently support the acceptance of alternative GH Cointegration hypothesis between both series. Thus, we can fairly conclude the existence of a regime shift in the long run relationship between CPO and FCPO level series.

Subsequently, we seek to examine the significance of these breaks in the cointegration regression between CPO and FCPO series within these three models. In Table 5.13, when we modelled the dummy intercept break without trend, all tested coefficients were found to be virtually significant. However, the intercept and dummy variable tend to be insignificant at any alpha value, when testing the second model (with break date equal to 16 May 2002). The full structural break model exhibited a uniform result with the first model with the findings displaying a strong significant result for all the tested coefficients, however, the intercept coefficient increased from 0.0145 (generated from Test 1) to 0.1441.In summary, we can conclude that earlier the GH cointegration test suggests a regime shift in both series level, however, later, we were able to establish the evidence to support the significance of the break in June 2002 with the long run relationship between the CPO and FCPO series. Hence, this evidence may lead to the conclusion that it is crucial to model the structural shift in cointegration relationship between both tested series.

5.3.3 BEKK-GARCH Estimation

Table 5.14: Maximum Likelihood Estimation Results

Coefficient	BEKK-GARCH	BEKK-GARCH SB
α_{0s}	-0.020481	-0.119361
	[0.41595]	[0.00000]
α_{0f}	-0.002272	-0.0792
	[0.93192]	[0.00024]
α_{1s}		0.09261
		[0.00000]
α_{1f}		0.05591
		[0.00956]
α_{2s}		0.029
		[0.00000]
α_{2f}		0.01156
		[0.80349]
C_s	-0.106206	-0.11778
	[0.41059]	[0.32218]
C_{sf}	0.47601	0.44783
	[0.00002]	[0.00486]
C_f	-0.000032	-0.00162
	[0.99979]	[0.99365]
$C1_f$		-0.00054
		[0.99209]
$C2_f$		-0.0007
		[0.99015]
$C3_f$		0.0009
		[0.99612]
$C4_f$		0.48649
		[0.00732]
A_s	-0.28932	0.32757
	[0.42202]	[0.57343]
A_{sf}	-1.01909	1.10778
	[0.00000]	[0.00000]
A_{fs}	-0.68887	0.63655
	[0.00509]	[0.10279]
A_f	0.08844	-0.14306
	[0.825425]	[0.80088]
G_s	0.18714	-0.191
	[0.234838]	[0.33663]
G_{sf}	-0.42696	0.36523
	[0.00017]	[0.08698]
G_{fs}	-0.26063	-0.19356
	[0.00000]	[0.05276]
G_f	-0.10775	-0.29306
	[0.182007]	[0.00282]
LR	-10744.54774	-10752.35608

$Q(1)_s$	50.662	34.39
	[0.0000]	[0.0000]
$Q(5)_s$	86.844	64.752
	[0.0000]	[0.0000]
$Q(10)_s$	134.905	107.097
	[0.0000]	[0.0000]
$Q(1)_f$	1.021	0.754
	[0.3120]	[0.385]
$Q(5)_f$	19.52	15.105
	[0.0010]	[0.0010]
$Q(10)_f$	49.413	43.97
	[0.0000]	[0.0000]
$Q^2(1)_s$	31.109	32.137
	[0.0000]	[0.0000]
$Q^2(5)_s$	38.34	69.01
	[0.0000]	[0.0000]
$Q^2(10)_s$	42.35	75.006
	[0.0000]	[0.0000]
$Q^2(1)_f$	2.73	0.409
	[0.1000]	[0.5230]
$Q^2(5)_f$	6.01	17.863
	[0.3050]	[0.0030]
$Q^2(10)_f$	13.591	29.841
	[0.1920]	[0.0010]

Notes:

P-values are reported in parentheses.

BEKK-GARCH represents the BEKK-GARCH without the structural break and the mean specification and variance specification are as follows:

Mean Specification

$$Y_t = \alpha_0 + \varepsilon_t,$$

Variance Specification

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

And, BEKK-GARCH SB represents the BEKK-GARCH with structural breaks in mean and variance specification.
The specification as follows:

Mean Specification

$$Y_t = \alpha_0 + \alpha_1 MD1_t + \alpha_2 MD2_t + \varepsilon_t,$$

Where:
$MD1_t$ =1 for t>09:11:1998 otherwise 0 and $MD2_t$= 1 for t>28:07:1999 otherwise 0 for CPO
$MD1_t$ =1 for t>01:12:1998 otherwise 0 and $MD2_t$= 1 for t>30:07:1999 otherwise 0 for FCPO

Variance Specification

$$H_t = C^{*'}C^* + \sum_{k=1}^{K} G_k^{*'} H_{t-1} G_k^* + \sum_{k=1}^{K} A_k^{*'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_k^* + \sum_{k=1}^{K} C1_k^{*'} D1_t C1_k^* + \sum_{k=1}^{K} C2_k^{*'} D2_t C2_k^* + \sum_{k=1}^{K} C3_k^{*'} D3_t C3_k^* + \sum_{k=1}^{K} C4_k^{*'} D4_t C4_k^*$$

Where:
D1f=1 for t>31:10:1996 otherwise 0, D2f=1 for t>02:07:2001 otherwise 0, D3f=1 for t>02:10:2001, and
D4f=1 for t>18:03:2008 for FCPO.

This subsection presents the variance and covariance estimation for both series generated from the BEKK-GARCH framework. Although in section 5.3.2.3 we established a significant break that was detected for June 2002 in both series cointegration relationships, to illustrate the implications of the break in volatility clustering estimation, we only adopt a simple intercept BEKK model not the VECM-BEKK model. This is because of the lower number of parameters estimated for the intercept BEKK model (13 parameters) compared to the VECM BEKK (25 parameters). Table 5.14 reports the parameter estimation results for both selected volatility models. The estimation for the BEKK-GARCH without structural breaks model is presented in the first column, then the BEKK-GARCH with structural breaks in mean and variance estimation results is presented in the second column. The first mean model's estimation failed to prove any significant results in its intercept. However, when structural breaks were taken into consideration in the mean model, the intercepts and those dummy variables (represent the structural breaks in mean) turned to be highly significant (refer to α_0 ,α_1, and α_2 for both CPO and FCPO). Further, the variance estimation findings postulate quite similar results in the CPO series. Both variance estimation models' results virtually failed to find any significant results in either the variances lagged term (refer to G parameters) or in its residual terms (refer to A parameters). However, when we modelled the breaks in the FCPO variances series a slightly different conclusion can be made.

The findings indicate that the FCPO variance is highly related to the innovation of its own variances lagged term (G_f coefficient) but there is no evidence for its own residuals term. This evidence simply means that the movement of FCPO volatility is highly dependence on its previous volatility movement. Additionally, the FCPO volatility was not influenced by the FCPO own shock. Surprisingly, among four break dummy variables (refer to $C1_f$, $C2_f$, $C3_f$ and $C4_f$ coefficients) in the FCPO variance specification, only C4 coefficient is proven to be strongly significant. This result proved that there is a significant structural break effect which located in the recent global financial crisis (18 March 2008) towards the current FCPO volatility movement. Nevertheless, when referring to the covariances estimation (see A_{sf}, A_{fs} ,G_{sf} and G_{fs}) , both models demonstrate identical evidence that the CPO and FCPO covariances are highly influenced by both the residuals and variance lagged term. The study further examines whether there is any implication of structural break into volatility persistency. Considerable empirical evidence does support the crucial role of a break in volatility clustering modelling, which may overemphasize the actual variance persistency (Aggrawal,Inclan and Leal, 1999; Malik, 2003; Fang, Miller and Lee, 2008; and Fang and Miller, 2008). It is worth noting that the evidence was generated from a simple ARCH or GARCH framework. When we look at the persistency, the FCPO persistency is consistent with the existing body of literature where the structural break reduced the variance persistency from 1.15 to 0.93 (the persistency parameters calculation can be found in Appendix J). This finding has proved that without the structural break in modelling the volatility clustering process leads to inaccurate persistency estimation results.

In contrast to the FCPO, the CPO variance persistency merely increased (from 0.95 to 1.08) when we modelled the breaks in its mean specification, not in the CPO variance (since no breaks were reported in the k_2 test result). It is noteworthy that this research applied a much more complex model, the BEKK model, as it was foreseen that the result may potentially provide a unique variance estimation feature rather than the other empirical evidence. In addition, the structural break BEKK model for the FCPO is able to overcome the serial correlation (See $Q(1)_f$) and ARCH effect (See $Q^2(1)_f$), but not for the CPO. Although the CPO failed to account for the serial correlation and ARCH effect, such results are still expected as the mean model is only run on the intercept not using the AR or MA mean model (used in Fang, Miller and Lee, 2008;and Fang and Miller, 2008). The finding asserts that when there is any structural break, it is an important element to include in the volatility clustering modelling as it influences the accuracy of volatility parameters estimation.

5.3.4 Hedging performance measurement results

5.3.4.1 Hedging performance: Minimum Variance Framework

Table 5.15: Minimum Variance Result

	BEKK-WOSB				BEKK-SB			
	Hedge Ratio[a]	Var(UH)[b]	Var(H)[c]	Min Reduction (%)[d]	Hedge Ratio[a]	Var(UH)[b]	Var(H)[c]	Min Reduction (%)[d]
	In-sample				**In-sample**			
Forecasting Day Ahead								
1	0.48	1.63542	1.06483	34.89%	0.39	2.45225	1.76838	27.89%
10	0.42	2.32705	1.8769	19.34%	0.42	1.8338	1.1543	37.05%
15	0.37	2.45552	2.09602	14.64%	0.43	1.64334	1.04916	36.16%
20	0.94	2.88068	0.13627	95.27%	0.23	5.42726	4.82302	11.13%
	Out-sample				**Out-sample**			
Forecasting Day Ahead								
1	0.46	1.47156	0.92233	37.32%	0.44	1.9484	1.23226	36.76%
10	0.53	3.64266	2.71159	25.56%	0.46	3.28122	2.46355	24.92%
15	0.51	2.9602	2.1275	28.13%	0.44	2.66728	1.9333	27.52%
20	0.5	2.11454	1.38795	34.36%	0.43	2.08219	1.43993	30.85%

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

The previous section discussed the variance-covariance estimation for the two BEKK models and we further proceed for the forecasting procedure within 1, 10, 15 and 20 days ahead. The upper panel presents both models hedging ratios and the hedging performance results within the in-sample, while the lower panel is for out of sample forecasting results. The BEKK-SB model estimated a much more consistent hedging ratio and achieved less similar risk reduction within 1,10 and 15 forecasting days ahead compared to the BEKK without structural break model. However, on 20 days ahead it gives unexpected results where the BEKK-SB hedging ratio was reduced to 0.23 and attained only 11.13% variance reduction via hedging. In contrast, the BEKK without SB registered a much higher ratio, which is near to unity and almost 100% risk reduction was achieved during the same forecasted days ahead. The result indicates that market participants need to hedge almost all their spot positions in order to get a maximum risk reduction of nearly 100% during the 20-dayforecasting period ahead. However, when we consider the structural break in the BEKK estimation model, the result infers that investors only hedge 23% of the spot position and obtain much lower risk reduction than in the non-break model.

The panel below (in Table 5.15) represents the forecasting results for the BEKK and BEKK-SB models within the out-sample period. Quite similar results were found in both models, where BEKK-SB forecasted a marginally smaller hedging ratio than the general BEKK model. The highest risk reduction was achieved during the 1-day forecasting period ahead with nearly 38% for the BEKK-SB model and 37% for the other BEKK model. However, the smallest variance reduction was attained at an average of 25% during the 10 days forecasting period ahead for both models. Based on the risk reduction results for the 1 and 10 days forecasting periods ahead, it implies that hedgers achieved 38% on the first day forecasting period ahead and 25% on the 10 days forecasting period ahead. Such evidence portrays that hedging performance changes over time. In contrast to the in-sample results, a much more stable hedging ratio was estimated for both models where the BEKK model generated within 0.50-0.56 while, the other model estimated 0.46-0.48.Similar consistency for the out-sample resultswere found in the variance reduction context for both the BEKK and BEKK-SB models.

Overall, the BEKK-SB model unfailingly portrays a more consistent range of hedging ratio and risk reduction for both the in-sample or out-sample forecasting procedure compared to the non-break model. We can generally infer a similar range of hedging proportions against the spot contract in the 1, 10, and 15 forecasting period ahead. However, the general BEKK model exhibits inconsistency and a wider range of in-sample hedging ratio vis-à-vis the out-sample one. In terms of hedging performance, none of the forecasting periods ahead drives the same trend of variance reduction in either the BEKK or BEKK-SB model. Based on the above findings, we infer that the structural break is vital in modelling the volatility clustering estimation process as the less similar variance-covariance parameters estimation, and leads to more consistent hedging ratio forecasting results. Hence, the consistency of the hedging ratio will further influence the hedging performance results where the percentage for minimum risk reduction was more stable (either in-sample or out-sample forecasting procedure), although the percentage was slightly lower than the non-break model in almost all cases. As such, without the structural break the hedging performance tends to be upward bias and gives an extreme range of hedging ratio. Consequently, the non-inclusion of structural breaks in the variance-covariance clustering model will not only affect the accuracy of persistency estimation but also severely affect the hedging ratio and its performance. An erroneous hedging ratio will provide a misunderstanding on the evidence of the precise proportion of the future position needed to be hedged against the spot contract and fallaciously evaluates the strategy performance. Such a scenario will lead to less accuracy on the risk management strategy, especially for market practitioners who wish to hedge in this commodity market.

5.3.4.2 Utility Function Result

Table 5.16: Utility Maximization Function

	BEKK-WOSB			BEKK-SB		
			In-sample			
Φ	**UHGUtility**	**HGUtility**	**UCH**	**UHGUtility**	**HGUtility**	**UCH**
0.5	-0.63436	-0.54364	-14.30%	-0.40858	-0.25504	-37.58%
0.75	-0.94130	-0.80564	-14.41%	-0.61400	-0.38619	-37.10%
1	-1.24824	-1.06764	-14.47%	-0.81942	-0.51733	-36.87%
1.25	-1.55518	-1.32964	-14.50%	-1.02483	-0.64848	-36.72%
1.5	-1.86212	-1.59165	-14.52%	-1.23025	-0.77962	-36.63%
1.75	-2.16906	-1.85365	-14.54%	-1.43567	-0.91077	-36.56%
2	-2.47600	-2.11565	-14.55%	-1.64108	-1.04191	-36.51%
2.25	-2.78294	-2.37765	-14.56%	-1.84650	-1.17306	-36.47%
2.5	-3.08988	-2.63965	-14.57%	-2.05192	-1.30420	-36.44%
2.75	-3.39681	-2.90166	-14.58%	-2.25734	-1.43535	-36.41%
3	-3.70375	-3.16366	-14.58%	-2.46275	-1.56649	-36.39%
			Out-sample			
Φ	**UHGUtility**	**HGUtility**	**UCH**	**UHGUtility**	**HGUtility**	**UCH**
0.5	-0.71805	-0.52252	-27.23%	-0.63077	-0.47053	-25.40%
0.75	-1.08807	-0.78845	-27.54%	-0.96418	-0.71219	-26.13%
1	-1.45810	-1.05439	-27.69%	-1.29759	-0.95385	-26.49%
1.25	-1.82812	-1.32033	-27.78%	-1.63100	-1.19552	-26.70%
1.5	-2.19815	-1.58627	-27.84%	-1.96441	-1.43718	-26.84%
1.75	-2.56817	-1.85220	-27.88%	-2.29782	-1.67884	-26.94%
2	-2.93820	-2.11814	-27.91%	-2.63123	-1.92050	-27.01%
2.25	-3.30822	-2.38408	-27.93%	-2.96464	-2.16217	-27.07%
2.5	-3.67825	-2.65002	-27.95%	-3.29804	-2.40383	-27.11%
2.75	-4.04827	-2.91595	-27.97%	-3.63145	-2.64549	-27.15%
3	-4.41830	-3.18189	-27.98%	-3.96486	-2.88715	-27.18%

Note: Utility Maximization function for hedging portfolio and unhedged portfolio using 15 days forecasting period ahead. The Utility quadratic function generated from equation 56 and the **Φ** denotes the degree of risk aversion for investors ranging from 0.5 to 3.0.The UCH represents the utility changes between the hedgers and non-hedgers (HGUtility-UHGUtility)/UHGUtility.

Alternatively, the hedging effectiveness measurement can possibly be investigated using the investor's utility function achieved in hedging. Table 5.16

illustrates the utility comparison between the non-hedgers and the hedgers within the in-sample and out-sample for selected models using equation number 56 in page 106. The analysis does not wish to seek the optimum utility function that can be achieved by investors but to identify the effects of a structural break, which may potentially be reflected in this performance measurement within a 0.5 and 3.0 range of investors risk aversion.

Both models display a similar trend where hedgers tend to achieve a much higher utility combination within the in-sample and out-sample than the non-hedgers. A contrary relationship was illustrated between the risk aversion parameter and the investors' utility comparison results in both models. For explanation, a higher risk aversion portrays those investors who dislike risk and do not accept additional risk unless they receive an acceptable return. In the investment world, a lesser risk will drive to a lower return, so it is expected that a higher risk aversion investor will have a smaller utility function (since the risk and returns are low). In contrast, a less risk adverse investor will have a higher risk and return function but much higher utility function. This happens because the risk aversion parameter is much smaller, thus, the higher return received will outweigh the risk part. As such, it is synchronized with theory where the level of risk aversion has the opposite relationship to the investor's utility functions.

Furthermore, the in-sample estimation results demonstrate an outstanding utility performance for the BEKK-SB compared to the non-break model. Similarly, in the out-sample analysis, where the BEKK-SB model still gives a better risk and return trade off result compared to the other model, albeit marginally. This evidence is further supported by the utility changes result where the BEKK-SB demonstrates an average of 37% utility improvement within the in-sample and almost 27% within the out-sample comparison analysis. Subsequently, the counterpart model only registers an average of 14% and 27.5% for the in-sample and out-sample, respectively.

Finally, the above findings conclude that hedgers may gain more risk and return trade off than the non-hedgers, and that modelling structural breaks in the volatility clustering process is proven to outcast the model without the break. Therefore, we further confirm the importance of breaks in these estimation processes, which then influences both hedging performance measurements.

5.3.5 Hedging Ratio and Performance Consistency Analysis

In the beginning of this chapter, the findings reveal a dynamic hedging decision made by hedgers and confirm that hedging will minimize the market participant's risk exposure. In addition, this section examines the effectiveness of hedging strategies across the examination period. Throughout 1996 to 2008, there were various unexpected events that we initially conjectured as having some implications on hedging effectiveness. For simplicity, to investigate the hedging effectiveness consistency within the sampling period, the research focuses on the risk minimization measurement rather than the utility maximization function. We proceed to segregate six sub-periods to cater for the Ex-ante Asian Financial Crisis (January 1996 to June 1997), During Asian

Financial Crisis (July 1997-August 1998), Ex-Post Asian Financial Crisis (August 1998-December 1999), Technology Bubble (January 2000-September 2001), Ex-Post Terrorist Attack (September 2001-December 2002) and Oil price volatility [January 2003 onwards:1a) Pre-Mortgage Sub Prime (Pre MSP): January 2003-December 2006 and 1b) Mortgage sub Prime or Global Economic Crisis: January 2007 onwards]. We begin with the hedging ratio then the risk minimization performance generated from theGeneral BEKK and BEKK with Structural Break models.

5.3.5.1 Hedging Ratio

Table 5.17: Statistical Properties for Hedging Ratio for general BEKK and BEKK with Structural break (Full Period).

	BEKKSB	**BEKK**
Mean	0.49119	0.49389
Median	0.50637	0.50041
Maximum	1.03234	1.20708
Minimum	-0.7192	-0.8013
Std. Dev.	0.2056	0.20637
Skewness	-0.8077	-0.746
Kurtosis	5.00509	5.55037
Jarque-Bera	909.151	1197.14
Probability	0	0
Sum	1616.5	1625.38
Sum Sq. Dev.	139.077	140.11

Based on the two BEKK estimation results, the study then computes the dynamic hedging ratio and the statistical properties presented in Table 5.17. The statistical information is divided into two panels where the first panel presents the BEKK with Structural break hedging ratio and the second panel is for the ratio estimated by the Non-structural break BEKK model. Referring to the unconditional mean and standard deviation estimation, both models indicate a similar result at about 0.49 for mean and 0.20 for standard deviation. In addition, both distributions are negatively skewed and have a non-monotonic distribution (similar result demonstrated in Yang and Allen, 2004 in the Australian Stock index futures market). The non-monotonic features are further validated in the strong rejection of the Jarque-Bera probability test. A unique range of distribution is generated when we consider breaks in the BEKK estimation, where the distribution range of the hedging ratio is much smaller (within -0.72 to 1.03) than the non-structural break one (-0.80 to 1.21). We further tested the stability of the hedging ratio using the ADF and PP procedures. The details of the results are presented in Appendix K. However, both unit root tests exhibit a stationary at I(0) features in both hedging ratio estimated models (same result demonstrated in Yang, 2001; Yang and Allen, 2004; Kroner and Sultan, 1993; Brooks *et al.*, 2002; Ford, Pork and Poshakwale, 2005; Mili and Abid, 2004) but contrary to Bailie and Myers (1991) where the hedging ratio is only stationary at its first difference. Using the above results, we can conclude that a non-normality characteristic is found in both estimated hedging ratios and that these ratios do not have any unit root problem. However, the non-inclusion of a break may lead to a wider range of ratios distribution compared to the inclusion one. This provides evidence of a smaller hedging ratio when the potential break is included in the hedging ratio estimation process. The hedging ratios plotting for both models are presented in Figure 5.3. The ratio plotting portrays the non-monotonic hedging decision overtime, as hedgers will revise their hedging position in response to the surrounding information.

Figure 5.3: Hedging ratio for General BEKK and BEKK-SB (Full Sample)

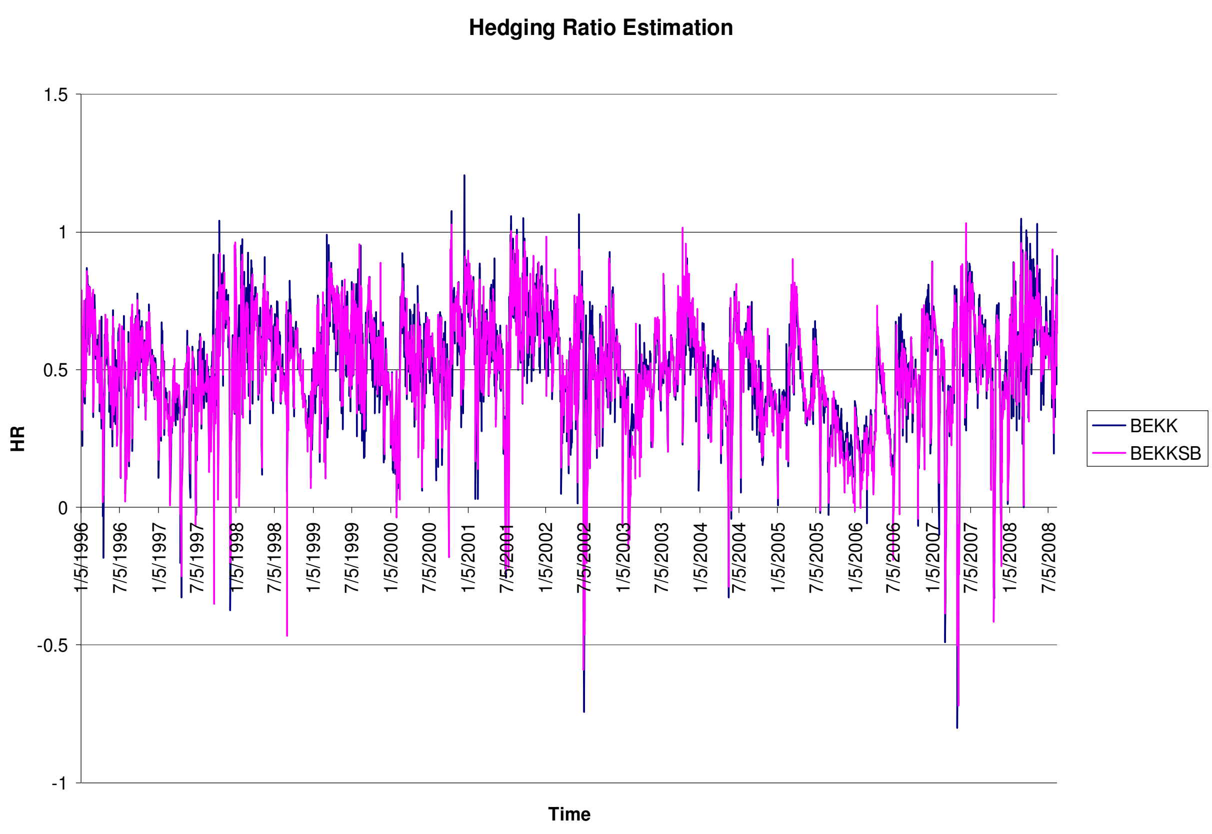


Table 5.18: Statistical Properties for general BEKK model Hedging Ratio.

BEKK	Pre-AFC	AFC	Post-AFC	TechnoBubble	Post-Terrorist Attack	Oil Price Vol	Pre-MSP	MSP
Mean	0.459847	0.567622	0.536095	0.549246	0.538311	0.451071	0.421852	0.522571
Median	0.478170	0.576674	0.538364	0.565697	0.557624	0.453742	0.419307	0.560978
Maximum	0.869967	1.040129	0.990045	1.207079	1.064152	1.048361	0.904959	1.048361
Minimum	-0.32669	-0.3744	0.056328	-0.255067	-0.743674	-0.801332	-0.32652	-0.80133
Std. Dev.	0.174661	0.200507	0.169622	0.213177	0.220645	0.206348	0.167550	0.266475
Skewness	-0.9639	-0.86717	-0.17167	-0.472917	-1.527017	-0.772882	-0.06863	-1.70133
Kurtosis	5.039764	5.222695	2.753541	3.904680	8.306371	6.062097	3.213355	7.607424
Jarque-Bera	128.3305	93.72367	2.731514	31.40586	537.2807	718.2055	2.789057	580.9474
Probability	0.000000	0.000000	0.255187	0.000000	0.000000	0.000000	0.247950	0.000000
Sum	179.8000	160.6369	196.7469	241.6681	185.1790	660.8186	438.7260	222.0926
Sum Sq. Dev.	11.89747	11.33723	10.53035	19.95004	16.69869	62.33626	29.16776	30.10788
Observations	391	283	367	440	344	1465	1040	425

Table 5.19: Statistical Properties for BEKK with Structural Break Model Hedging Ratio.

BEKK-SB	Pre-AFC	AFC	Post-AFC	TechnoBubble	Post-Terrorist Attack	Oil Price Vol	Pre-MSP	MSP
Mean	0.466384	0.543133	0.536897	0.555603	0.546706	0.443849	0.414063	0.516738
Median	0.484227	0.554686	0.539972	0.572435	0.563624	0.454923	0.417291	0.563579
Maximum	0.857110	0.960395	0.954579	1.027666	0.983017	1.032342	1.014273	1.032342
Minimum	-0.25132	-0.35064	-0.4653	-0.23467	-0.589266	-0.719202	-0.2872	-0.7192
Std. Dev.	0.163795	0.194137	0.172877	0.204732	0.215729	0.210265	0.184070	0.249251
Skewness	-0.76542	-1.08593	-0.63378	-0.808296	-1.459861	-0.71888	-0.11107	-1.80122
Kurtosis	4.401690	5.607473	5.239922	4.504813	7.389012	4.862267	2.995639	7.750043
Jarque-Bera	70.18771	135.7916	101.2913	89.42692	398.2975	337.8773	2.139290	629.3616
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.343130	0.000000
Sum	182.3562	153.7067	197.0414	244.4654	188.0669	650.2391	430.6255	219.6136
Sum Sq. Dev.	10.46327	10.62833	10.93843	18.40072	15.96281	64.72527	35.20326	26.34138
Observations	391	283	367	440	344	1465	1040	425

The statistical properties for hedging ratio estimated in the general BEKK and BEKK with structural breaks are represented in Tables5.18 and 5.19, respectively. The consistency of hedging decision made by hedgers over the sample period is examined through the statistical properties within six sub-periods. The above finding clearly demonstrates an upwards bias for the hedging ratio generated in the BEKK model vis-à-vis the BEKK-SB model during the volatility sub-periods (include in AFC, Oil price volatility, Pre MSP and MSP). The highest difference of hedging ratio was registered during the Asian Financial Crisis where the non-break model suggests that hedgers should hedge an average of 56.7% of the CPO position while the break model indicates only 54%. The average lowest hedging proportion is shown during the pre Mortgage Sub Prime period, at 41% for the BEKK-SB model and 42% for the general model. In contrast, the general BEKK model tends to give a slightly lower hedging ratio mean during the tranquil market sub-periods. In addition, the structural break model obviously estimated a smaller range of hedging ratio than the non-break model. Hence, it is expected that the unconditional second moment of the ratio is much lower at all sub-periods compared to its counterpart model.

As for the third moment, the results indicate a similar finding for both models where the distribution of hedging ratio is more towards the negative tail. Subsequently, during the Asian Financial Crisis period the non-break model exhibits normal distribution features in the Kurtosis and the Jarque-Bera Probability test results. However, the results turned to become non-normal when the structural breaks were taken into account. Similar to Ford, Pok and Poshakwale (2005), we found that a higher hedging ratio was generated during the Asian financial crisis sub-period compared to other sub-period ratios. They estimated the hedging ratio in the KLCI stock index futures within the general BEKK model, while we investigated the hedging ratio in the CPO commodity market using both general BEKK and BEKK with structural break models.

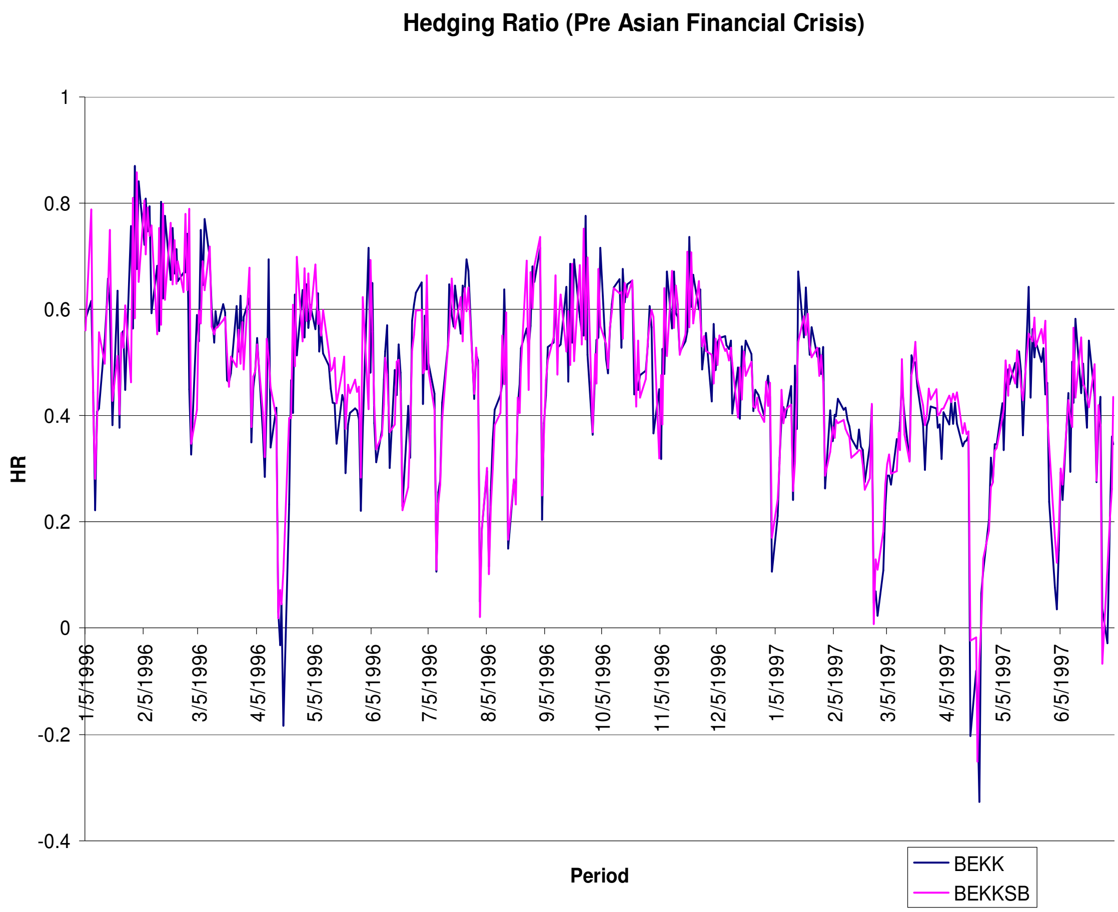
Figure 5.3 shows the hedging ratio generated from both models according to sub-periods. The hedge ratio can be less than 1, 1 or more than 1 in either the minimum variance or the mean variance framework (Karp, 1986). We can see that some of the hedging ratios are not constantly positive. Yang (2001) also infers a non-positive hedging ratio generated in the Australian Stock index futures market. Ederington (1979) specifies that an opposite relationship between spot and futures prices will estimate a non-positive hedging ratio. Therefore, these negative hedging ratios are generated when the correlation between the CPO and FCPO series is inversely correlated. When we relate to internal or external events, we can conclude that the negative hedging ratios were during the CPO production stress period. As for external events, the figure demonstrates a few negative cases during the Asian Financial Crisis in 1997 and the Global economic downturn with the food crisis in 2007. Taking as an example 2007, three negative ratios were found including -0.46 in March, -0.80 in May and -0.41 in October. Intuitively, the ratios indicate that hedgers should hedge 46% of their CPO position in March, 80% in May and 41% in October. During these negative periods, the refiner must go long in both markets while for the producers' position a contrary strategy is required. Other than the periods mentioned, almost 99% of the hedging ratio generated a positive value.[23] Similarly, Brooks *et al.* (2002) infer a non-negative close to unity hedging ratio for both the symmetric and asymmetric BEKK model.

Generally, the statistical properties indicate that the non-break model tends to overestimate the hedging decision during volatile markets compared to the BEKK-SB model. As such, it is important to model the structural break (if any) in the volatility clustering specification so that a more accurate hedging ratio can be generated. Omissions of these breaks will tend to estimate a spurious hedging proportion and lead to less effective hedging performance. While, the plotting of hedging ratios strongly supports the dynamic process of hedging decision over time (similar to Mili and Abid, 2004; Bera*et al.*,1997; Yang, 2001; Kumar *et al.*,2008), the ratios tend to be more volatile for certain periods and stable at other times. The dynamic process is relevant since a lot of information consisting of internal and external events may affect the CPO market volatility. Therefore, market participants use this information and revise their hedging strategy so that the strategy gives the most effective results in managing risk.

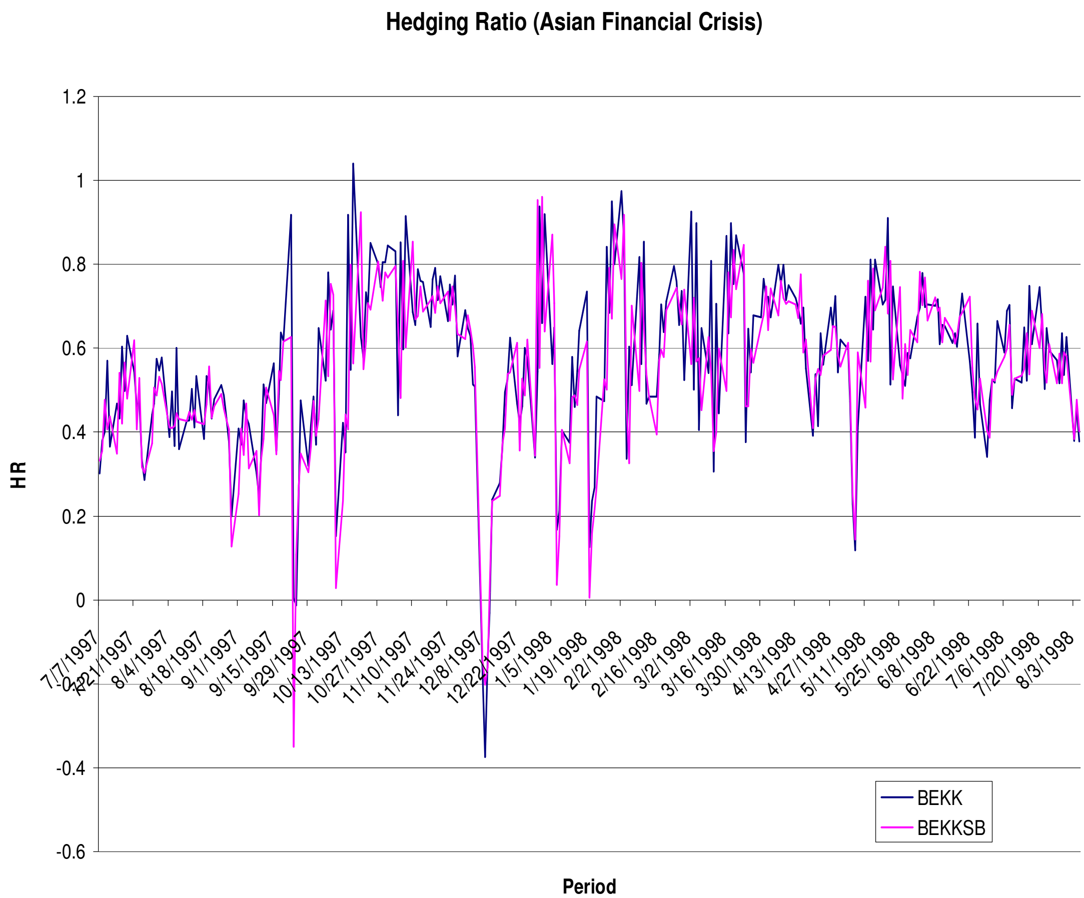
[23]Similar to Kumar et al. (2008).

Figure 5.4: Plots for the Hedging Ratios According To Six Sub-periods

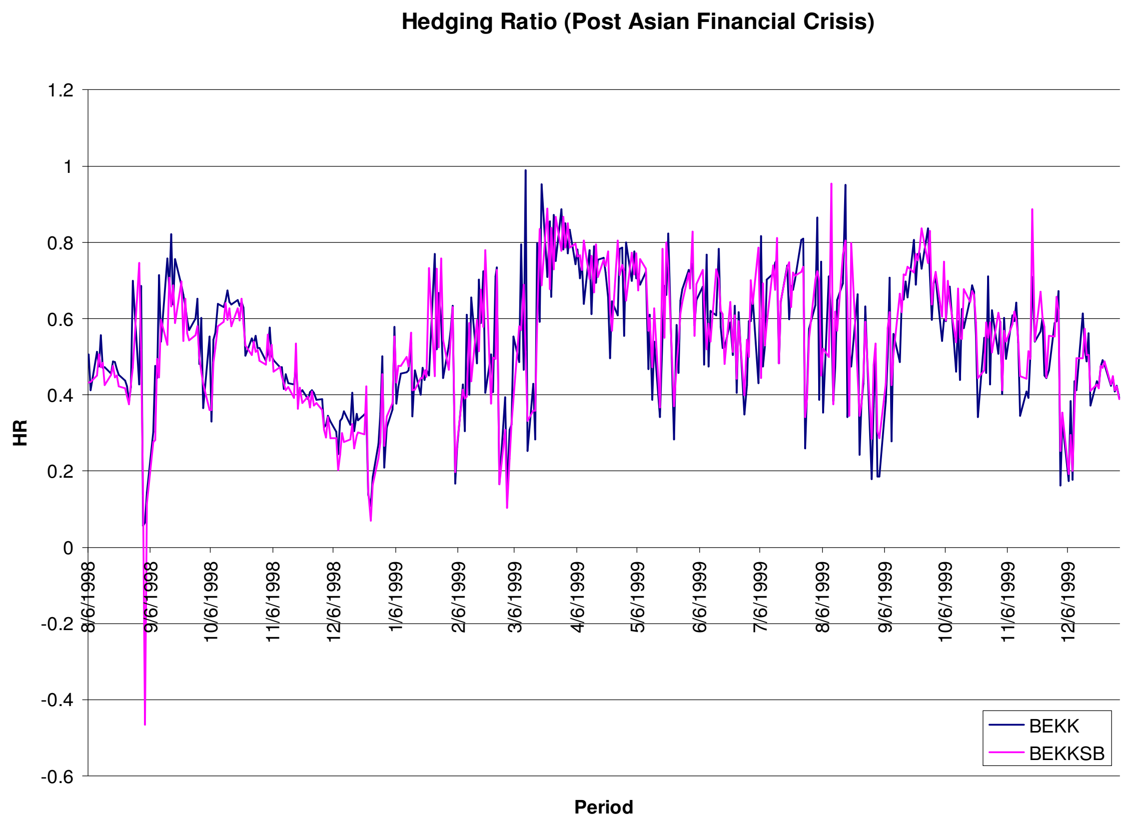
5.4 a) Pre Asian Financial Crisis Period



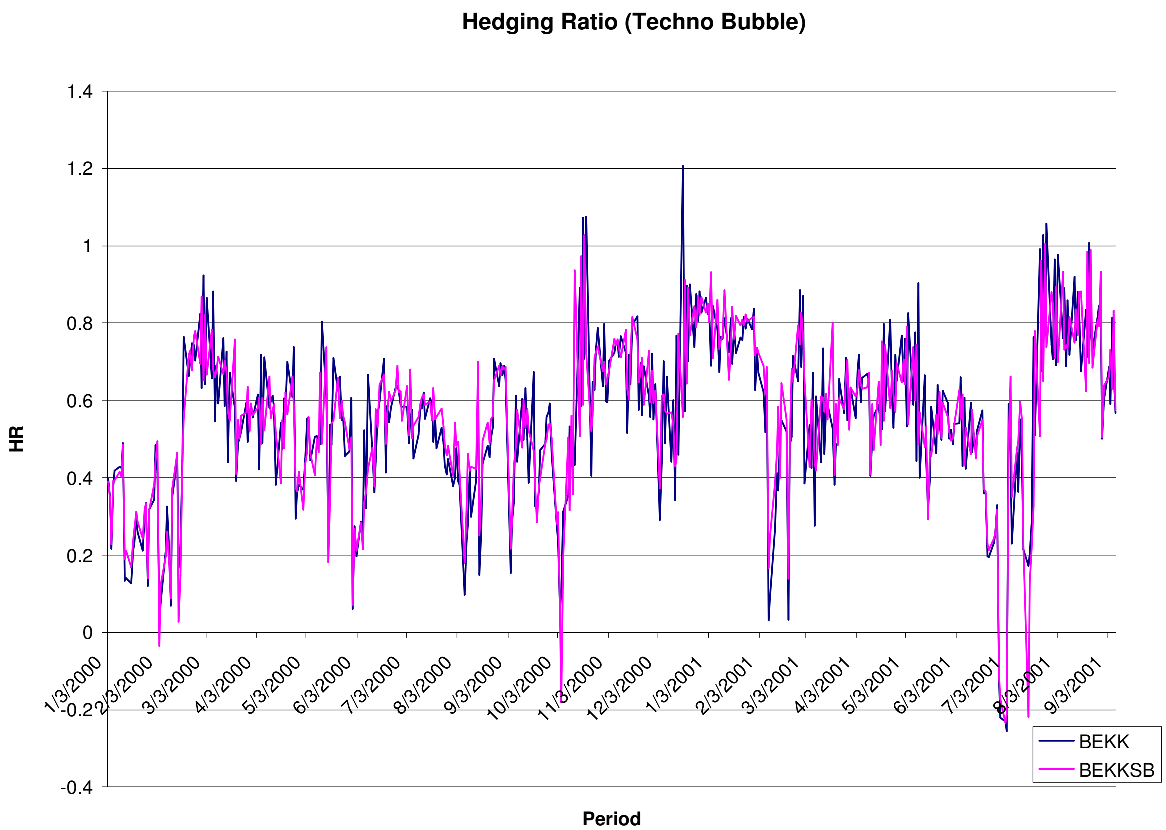
5.4 b) During Asian Financial Crisis Period



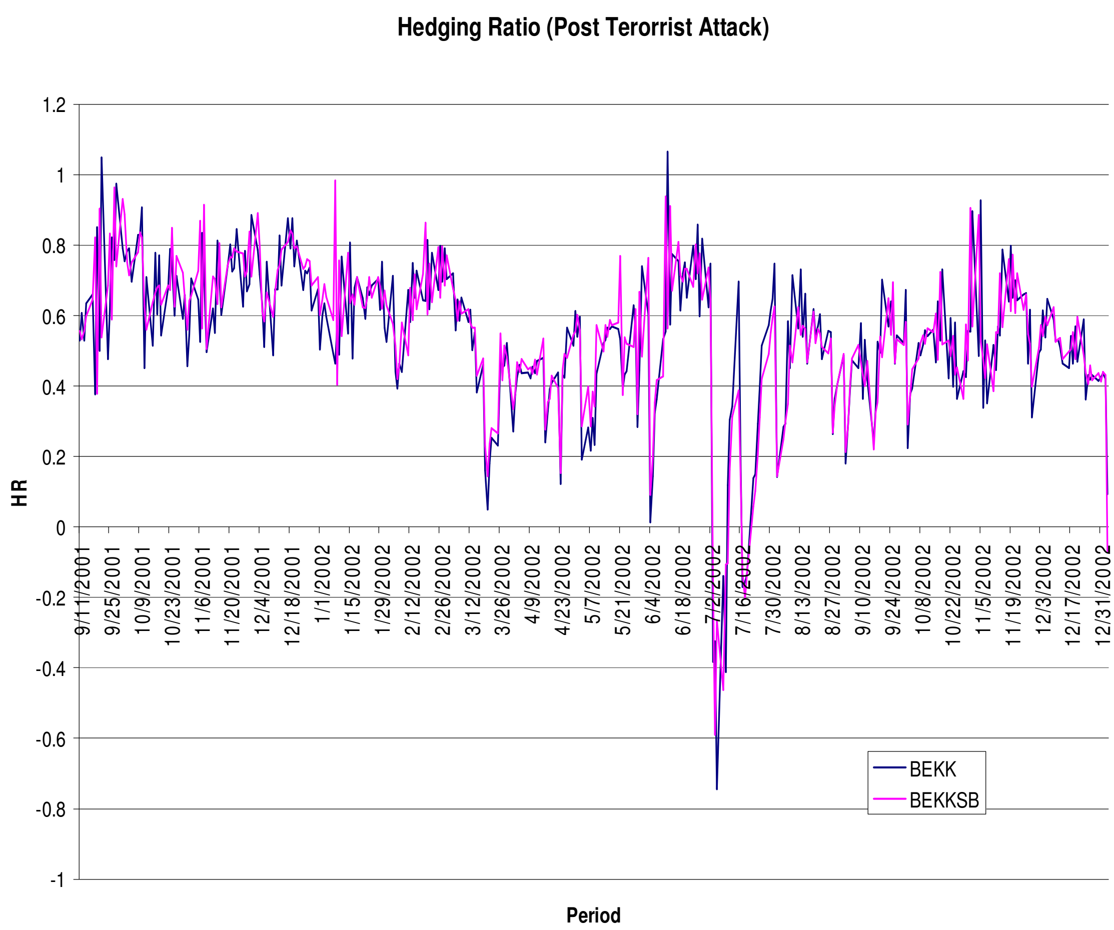
5.4 c) Post Asian Financial Crisis Period



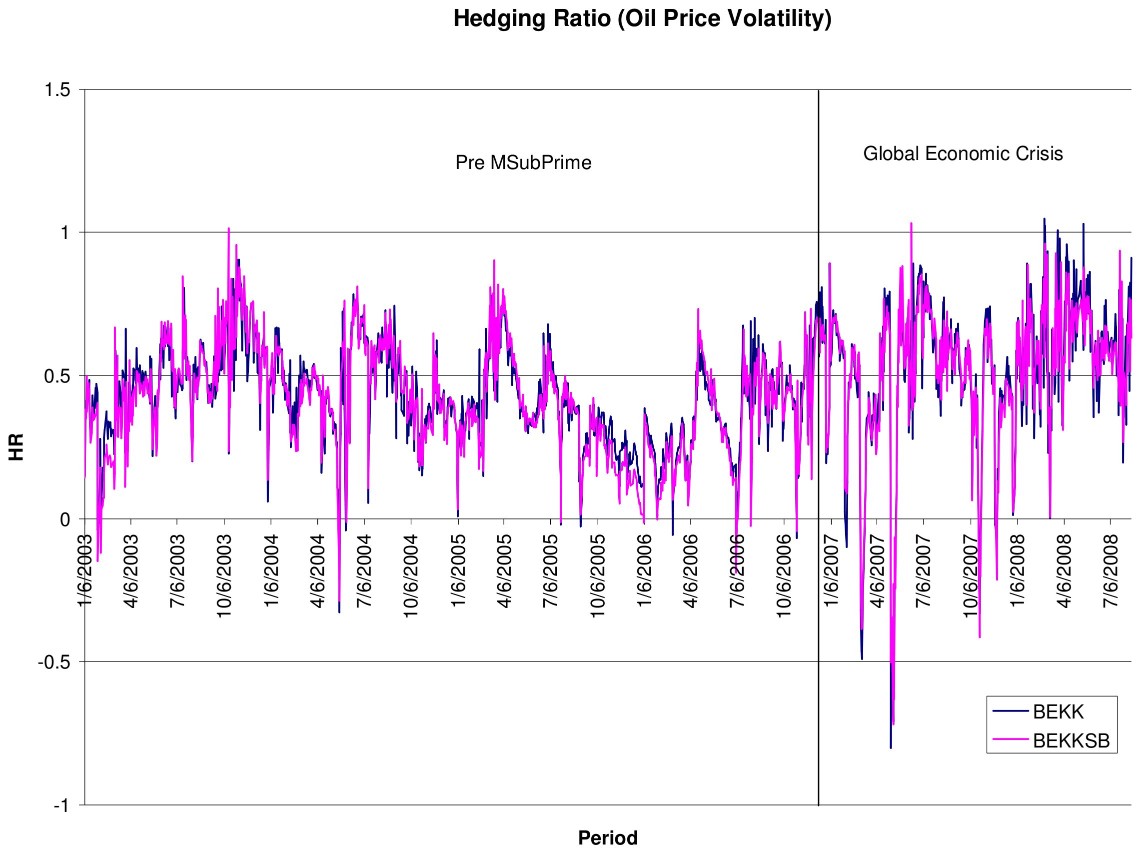
5.4 d) Technology Bubble Period



5.4 e) Post Terrorist Attack Period



5.4 f) Oil Price Volatility (Pre MSP and Global Economic Crisis)



5.3.5.2 Hedging Risk Reduction Performance

Table 5.20: Statistical Properties for risk reduction for general BEKK model

BEKK	Pre-AFC	AFC	Post-AFC	TechnoBubble	Post-Terrorist Attack	Oil Price Vol	Pre-MSP	MSP
Mean	0.296927	0.415644	0.366416	0.392438	0.389130	0.296686	0.255871	0.396563
Median	0.304849	0.418524	0.356016	0.391384	0.389312	0.275900	0.236479	0.400335
Maximum	0.648599	0.835430	0.746699	0.838757	0.782094	0.791021	0.722023	0.791021
Minimum	0.000545	6.79E-05	0.008200	0.001134	0.000346	9.59E-07	0.000131	9.59E-07
Std. Dev.	0.146746	0.174701	0.166909	0.194533	0.173669	0.173238	0.151505	0.182460
Skewness	0.027532	-0.20313	0.054742	-0.026445	-0.184152	0.431463	0.554085	-0.14776
Kurtosis	2.461738	2.459548	2.215328	2.344985	2.443251	2.536663	2.826682	2.446121
Jarque-Bera	4.769525	5.390367	9.598539	7.917093	6.387180	58.55854	54.51683	6.979124
Probability	0.092111	0.067530	0.008236	0.019091	0.041024	0.000000	0.000000	0.030514
Sum	116.0985	117.6272	134.4748	172.6729	133.8608	434.6455	266.1063	168.5392
Sum Sq. Dev.	8.398372	8.606790	10.19624	16.61318	10.34517	43.93671	23.84907	14.11565
Observations	391	283	367	440	344	1465	1040	425

Table 5.21: Statistical Properties for risk reduction for BEKK with Structural Break

BEKK-SB	Pre-AFC	AFC	Post-AFC	TechnoBubble	Post-Terrorist Attack	Oil Price Vol	Pre-MSP	MSP
Mean	0.302794	0.382069	0.375684	0.403691	0.400251	0.297135	0.259775	0.388557
Median	0.307258	0.388399	0.367554	0.405299	0.401511	0.287043	0.242371	0.407974
Maximum	0.658243	0.774562	0.791460	0.816377	0.795097	0.773722	0.764832	0.773722
Minimum	8.79E-05	3.18E-05	0.006096	0.000503	0.003975	8.71E-06	8.71E-06	2.23E-05
Std. Dev.	0.143558	0.177585	0.172468	0.195320	0.177366	0.178558	0.165352	0.176879
Skewness	-0.07113	-0.15838	0.087474	-0.063033	-0.16606	0.270593	0.467598	-0.28405
Kurtosis	2.572420	2.206425	2.288669	2.293318	2.449707	2.262245	2.571502	2.428864
Jarque-Bera	3.308245	8.609031	8.205479	9.447023	5.921474	51.10196	45.85544	11.49156
Probability	0.191260	0.013507	0.016527	0.008884	0.051781	0.000000	0.000000	0.003196
Sum	118.3924	108.1254	137.8761	177.6242	137.6865	435.3030	270.1661	165.1369
Sum Sq. Dev.	8.037418	8.893283	10.88669	16.74782	10.79035	46.67679	28.40770	13.26533
Observations	391	283	367	440	344	1465	1040	425

The previous section discussed the consistency of hedging ratios within the six sub-periods, while this section demonstrates the consistency of hedging performance within the same sub-periods. Note that for hedging performance consistency analysis, we used the minimum variance measurement, which focuses on the degree of risk reduction that can be achieved via hedging. The statistical properties for hedging performance are summarized in Table 5.20 for the General BEKK model and Table 5.21 for the BEKK-SB model. Similar to the hedging ratio results, we found that the BEKK model tends to overestimate the hedging performance more than the break model during the Asian financial crisis and global economic recession period. Subsequently, in less volatile periods either the BEKK or BEKK-SB give almost similar performances (Ex-Ante Mortgage Sub Prime). However, the break model tends to marginally outperform the BEKK model in the Pre and Post Asian Financial Crisis, Post Terrorist Attack and Technology Bubble. The BEKK model reached its peak performance (at 41.5%) in the Asian Financial Crisis sub-period, while the break model achieved a 40% average risk reduction in the Technology Bubble and Post terrorist attack period. Both models exhibit the lowest risk reduction (at almost 26%) during the period prior to the Mortgage Sub Prime sub-period.

Based on the overall average risk reduction results, we observed that CPO hedgers can reduce their price risk exposure between 26% to 41.5% of the unhedged portfolio. This range of percentages is considered a good range of hedging performance as most developed commodity markets display much lower risk reduction than in this CPO market (see Bera *et al.* (1997), Yang and Awokuse (2002), Chan and Young

(2006), in most developed commodity markets).[24] Virtually, both models share the same trend cycle for average hedge performances constantly throughout all sub-periods.

The second moments for both models were found to be similar for all sub-periods except for the Post Asian Financial Crisis, Pre Mortgage Sub Prime and recent Global Recession sub-periods. However, the general BEKK model estimates a wider range of hedging performance than the break model in more volatile markets (during the Asian Financial Crisis, Oil price volatility – Global Economic recession). A contrary range of performances was demonstrated during the calmer sub-periods. The kurtosis results tend to portray a platikurtic distribution for both the BEKK and BEKK-SB model, while similar skewness patterns were found in both estimated models for all the sub-periods, except during the pre Asian financial crisis where the distribution generated by BEKK was positively skewed; it was negatively skewed for the BEKK-SB model. The Jarque-Bera probability results exhibit a contrary conclusion during the Pre Asian Financial Crisis between both models. The non-break model significantly rejects the normality features but not for the counterpart model. In addition, the other sub-periods infer the non-normality features in hedging performance generated from both models.

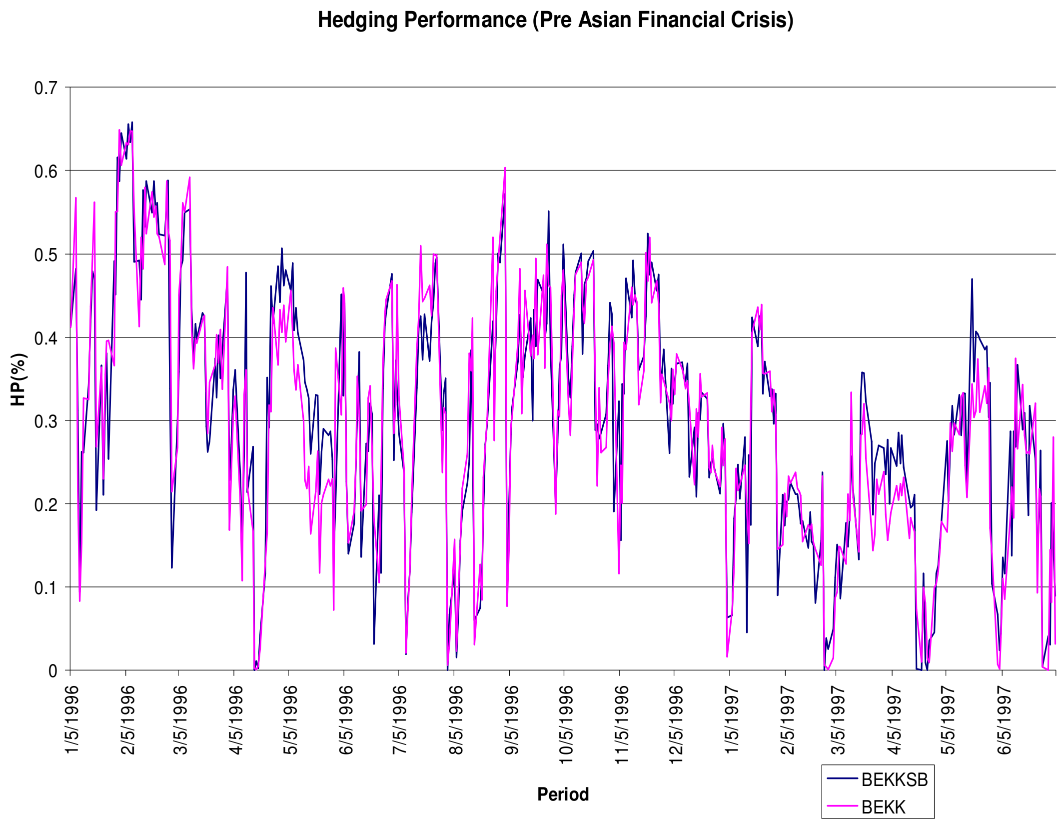
[24]Risk Reduction in various commodity markets:
Baillie and Myers (1991): Beef <10%, Coffee, Corn and Cotton <25%, Gold 30% and Soybean 56%.
Bera et al. (1997): Corn and Soybean >65% (within in-sample) and 0.87%-69% (within out-sample).
Chan and Young (2006): Copper 2%-10% within in-sample and 2%-11% within out-sample estimation.
Yang and Awokuse (2002): Soybean, Cotton, Sugar, Feeder Cattle <27%, Corn and Hogs 52% and Wheat 66%.
Lien and Yang (2007): Corn 27%, Soybean 12%, Cotton 16%-26%, Coffee 52% - 68%, Pork Belly 43% – 65%, Hog 35%-40%, Heating Oil 72%-82%, Crude Oil 22%-31%, Copper 13%-26% and Silver 1.4%-9%.

The hedging performance plotting (risk reduction) estimated from both models, segregated according to the sub-periods, is presented in Figure 5.5. The Pre and Asian Financial Crisis, Global economic crisis periods tend to exhibit an extreme movement of risk reduction fluctuation experienced by hedgers, more so than the other sub-periods. It was also found that during February 1998, the CPO hedgers were able to achieve the highest risk reduction, which was 83% for all sampling periods. Another 78% variance reduction was achieved in both July 2007 and April 2008. However, the plotting reveals that hedging was not always able to achieve a constant risk reduction (the lowest risk reduction was attained in May and August 1996, March, June and October 1997, September 1998, February and October 2000, February 2001, April 2002, February 2003, January and July 2005, February, March, October, November and December 2007 and March 2008). Based on the evidence, a dramatic fluctuation of hedging performance from highest to almost no protection against the CPO price risk was experienced by hedgers, especially during the Asian Financial Crisis and Global Economic recession sub-periods. In addition, a more stable but dynamic hedging performance was achieved during the other sub-periods.

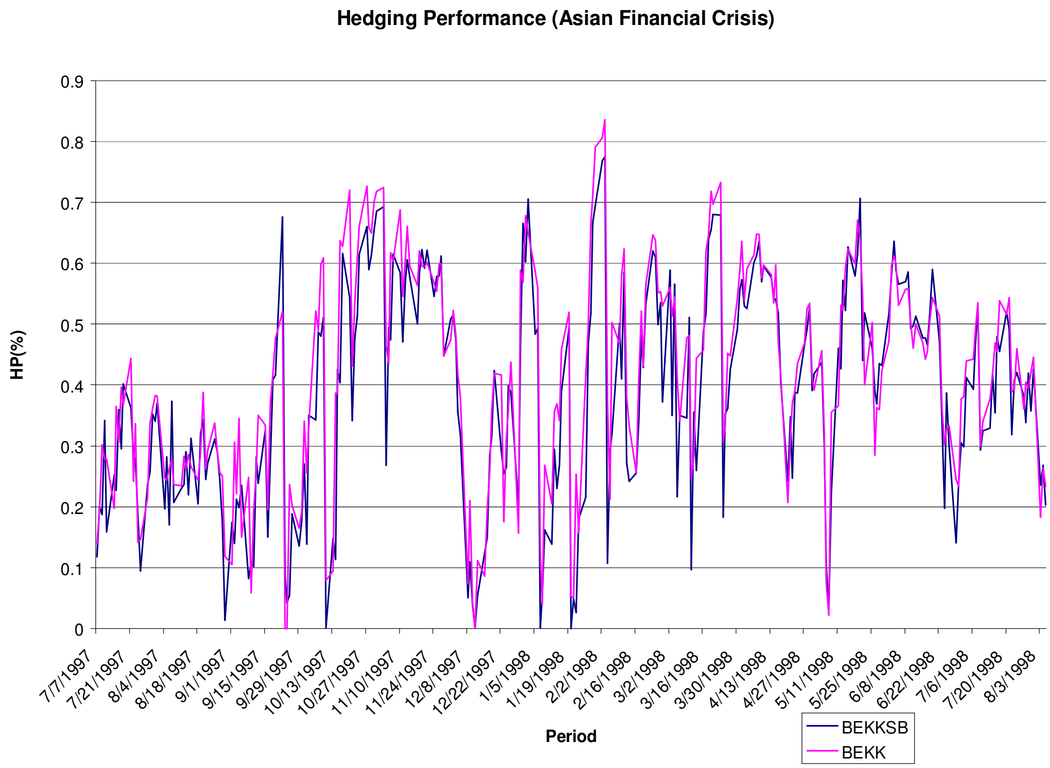
In summary, the above findings infer that the break model's hedging performances converge to the non-break model estimation when the market is calmer. When the market is volatile, the break model gives more stable hedging performance estimation (small range of minimum and maximum risk reduction) than the non-break model (bias risk reduction measurement during the Asian Financial Crisis and Global Crisis).

Figure 5.5: Plots for the Hedging Performances according to six sub-periods.

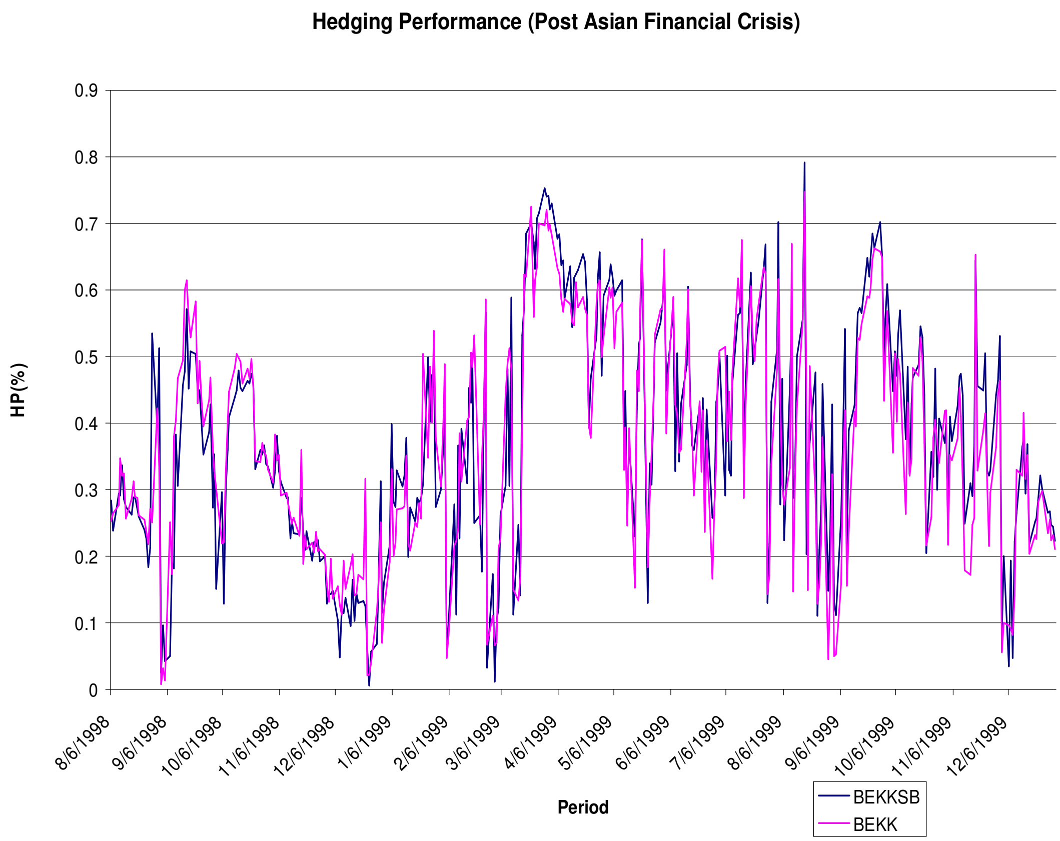
5.5 a) Pre Asian Financial Crisis Period



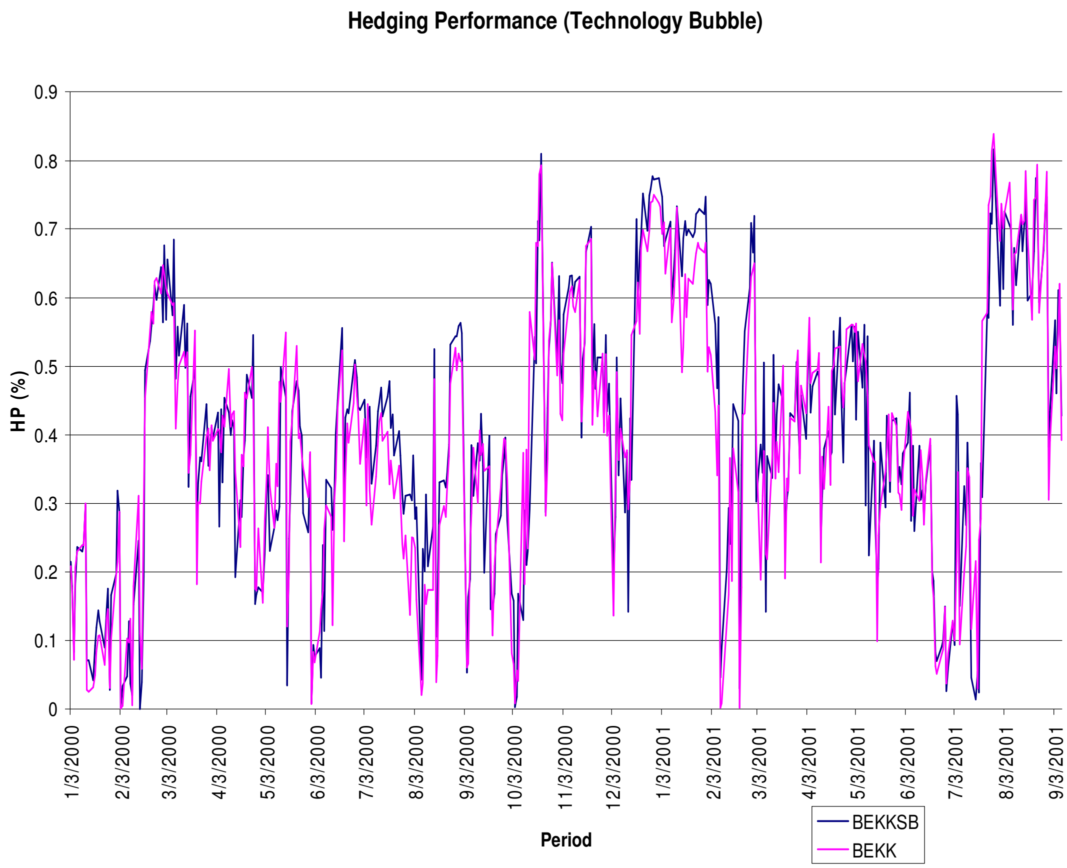
5.5 b) During Asian Financial Crisis Period



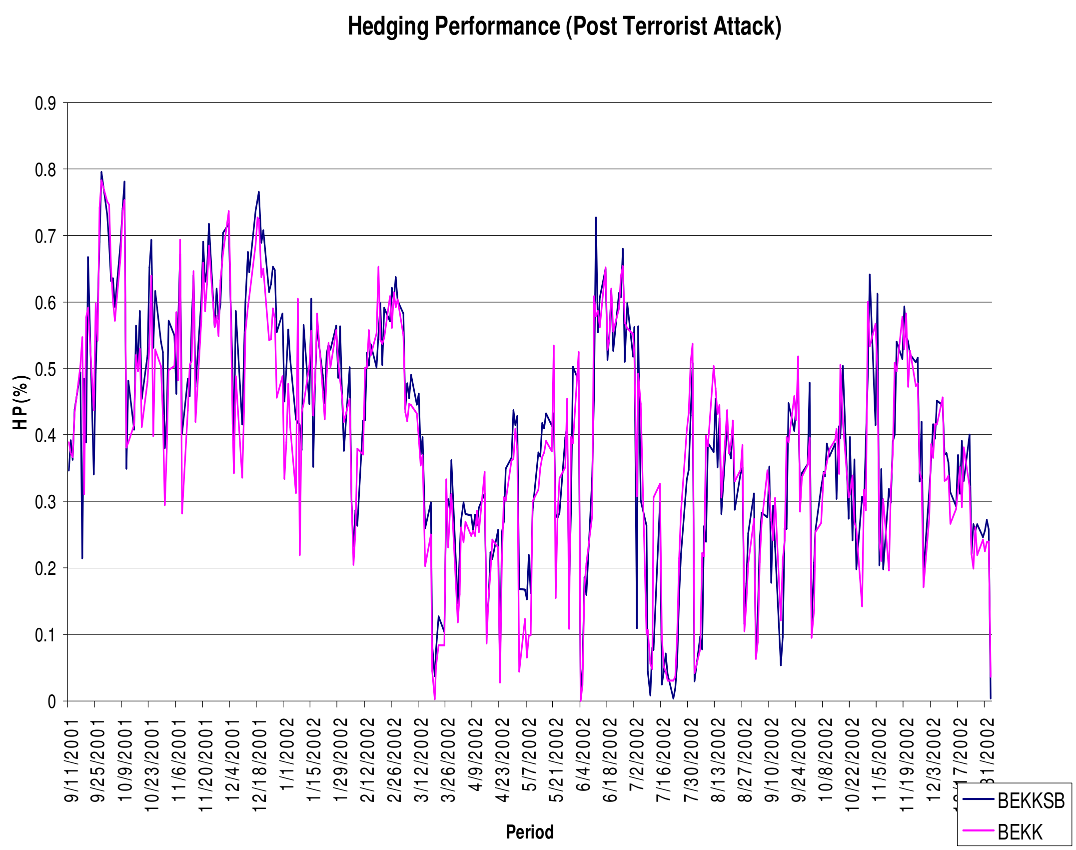
5.5 c) Post Asian Financial Crisis Period



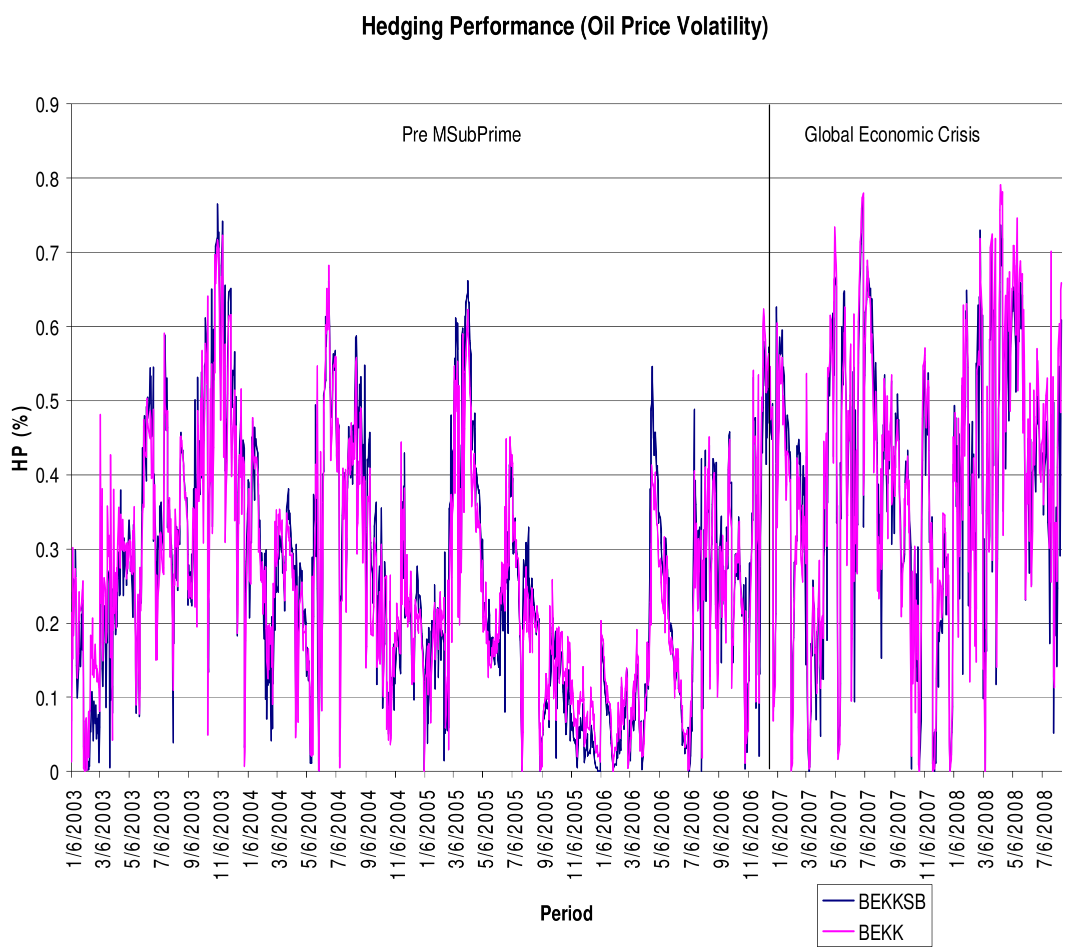
5.5 d) Technology Bubble Period



5.5 e) Post Terrorist Attack Period



5.5 f) Oil Price Volatility Period (Pre MSP and Global Economic Crisis)



5.3.6 Conclusion

This study extended the structural change analysis in the Malaysian CPO and FCPO market. Our analysis acknowledges the presence of structural breaks in the series mean, variance and also in both series long run relationships. The investigation further adopted the three structural breaks techniques consisting of the Bai and Perron procedure for mean, both the IT and modified ICSS algorithm for variance; and lastly, the GH cointegration was tested in series level long run equilibrium. This study investigated the implications in persistency estimation parameters when we omitted the identified break detected in both the CPO and FCPO return series. Ultimately, the study extends the structural break effect to the hedging performance measurement evaluation process.

The findings discovered two structural changes in both the CPO and FCPO return means around late 1998 and 1999. In addition, the ICSS test results identified significant large numbers of regime changes in the variance series. The IT ICSS and k_1 test results substantiate more breaks for both series compared to k_2(similar to Sanso *et al*., 2004). The results of the three tests exhibit structural changes between 1997 and 1998, late 2001, 2002, between 2005 and 2006 and, ultimately, 2008. It is a formidable task to model all the breaks detected in the IT and k_1 test results. Therefore, for the purpose of the volatility modelling procedure we confidently selected the breaks identified by the k_2 test dated late 1996, late 2001 and early 2008 (only applicable to FCPO).

Obviously the mean experienced some regime changes after the Asian financial crisis, however, the variance underwent shifts pre and during the crisis. In addition, externally, the variance suffered more changes during the post-terrorist attack, oil price shock and recent global economic crisis. Furthermore, the changes are attributable to the uncertain production level caused by a lower biological cycle for the palm trees, production level of other vegetable oil producers and weather volatility. Similarly, changes in both CPO and FCPO mean were observed as a result of the CPO outstanding production performance. However, the structural changes in variance were merely triggered by the stable demand forces. Meanwhile, the long regime shift test validated a significant change in its long run relationship for mid-June 2000 (proven in both 1 and 3 GH models). Ultimately, the volatility clustering finding gives very distinctive evidence where the CPO variance does not reduce when the structural breaks were taken into account in the model. However, the FCPO variance exhibits alower persistency estimation when the structural changes were considered. Similar to macroeconomic and financial variables, our findings support the importance of testing these structural break identification techniques before modelling the commodities volatility behaviour accurately.

Using a parsimony GARCH model, the study extends to display the consequences of omitting breaks in the hedging performance context. The research proceeds to test the significance of the effect of breaks on the hedging ratio and hedging performance accuracy. Within the minimum variance and mean variance framework, the results validate that the break model tends to estimate a steadier hedging ratio and performance. Additionally, hedgers hedged an average of above 50% in most sub-periods except in the Pre Asian Financial crisis, oil price volatility and pre global economic crisis (Pre-MSP). Furthermore, the general BEKK model indicates that the highest average risk reduction was achieved during the Asian Financial Crisis period. However, the break model exhibited that the Post Terrorist Attack and Technology Bubble period both experienced most of the risk reduction performance. Overall, when the CPO market is less volatile, the non-break model tends to give a downward bias hedging ratio and hedging performance estimation. In contrast, results were found during amore volatile market. In conclusion, the findings prove that less accurate hedging performance measurements result if we omit the potential break existing in the tested series. Further, we can understand that hedgers will revise their hedging decision according to the information arriving on the market. We further find that hedging strategy consistency is able to fulfil its theoretical objective (minimizing price risk), although hedgers received almost no protection within the tested period other than in isolated cases.