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The effect of regime shift in minimum variance hedging ratio: the evidence of the crude palm oil market

Abstract

Many suggest that ignoring regime shifts tends to estimate an upward bias persistency parameter in many macroeconomic and financial returns series. This paper introduces the effect of regime shifts in hedging ratio and hedging performances for the crude palm oil (CPO) market. To detect the presence of any regime shifts in both series mean and variance, the Bai and Perron and adjusted Inclan and Tiao Iteration cumulative sum of squared algorithm procedures were employed. The analysis further includes these regime shifts dummies into the volatility clustering modelling process and estimates the minimum variance hedging ratio and risk minimization. The findings infer that by taking into consideration these regime shifts in the volatility clustering estimation process, it estimates a more accurate proportion spot position that needs to be hedged and, furthermore, gives better hedging performance results. Without regime shift, the model specifies that CPO participants need to rebalance their hedging proportions more often compared to the regime shift model.

Keywords: Regime shift, hedging ratio, risk minimization, CPO.
JEL Classification: C50, G10, Q10.

Introduction

Statistics[1] portray a larger uncertain fluctuation in palm oil price compared to soybean and sunflower oil. Furthermore, the price volatility in these commodity markets may lead to unlimited profitability or losses for the market players. Therefore, managing this unfavorable price movement is more crucial for palm oil market players compared to the other vegetable oil players. Additionally, price volatility in the commodity market directly influences the economic performance of emerging countries (Eichengreen, 2002). Hence, the palm oil market players should protect this uncertain price movement via a hedging strategy.

By definition, the hedging decision is synonymous with the hedging ratio that shows the proportion of futures contracts against the spot market. Traditionally, the hedging ratio is known to be constant (Ederington, 1979). However, the hedging ratio or 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). Practically all hedging decisions are likely to change over time. Empirical evidence confirms the rationality of the non-monotonic characteristic of hedger's decisions because they can then change the hedging percentage based on the information available in the market. Fung et al. (2006) infer that fund managers tend to make non-static hedging decisions and they tend to change their hedging strategies to correspond to the risk factor in a changing environment. The environment changes are influenced by the internal (domestic) or external factors (international). Many researchers have empirically determined the presence of a regime shift in various macroeconomic series. Most concentrate on the international context (see Fang, Miller and Lee, 2008; Fang and Miller, 2008; Rapach and Strauss, 2008; Andreou and Ghysels, 2002), while others combine between domestic and international contexts (refer to Aggrawal, Inclan and Leal, 1999; and Zhang, Russel and Tsay, 2001; Salisu and Mobolaji, 2013). However, very few studies have explored the significance of structural breaks (or regime shifts) within emerging spot and futures commodities prices.

Over the years, many studies have attempted to identify the best measurement that has captured the hedging performance in various futures markets within the mean variance and minimum variance framework. The studies explored various ranges of measurements from a conservative OLS approach (static hedging ratio) to the MGARCH modelling specifications (dynamic hedging ratio). Most of the existing empirical literature modelled the strategy effectiveness estimation in various futures markets (Laws and Thompson, 2005; Yang, 2001; Brooks et al., 2002; and Ford, Pok and Poshakwale, 2005), the stock market (Graf, 1953; Bailie and Myers, 1991; and Bera, Gracia and Poh, 1997; and Mili and Abid, 2004), the commodity market and other financial instruments *inter alia* (Ederington, 1979; and Wilkinson et al., 1999). The evidence supports the outstanding performance of a dynamic hedging measurement compared to a static hedging measurement.

On a different perspective, Lien (2005) specifies three elements that may potentially make the hedging ratio estimation less accurate these being: (1) a smaller sample size, (2) the presence of a regime shift in the tested series and, finally, (3) inconsistent criterion specified in the estimated and

[1] 8.5%, 0.59%, 1.83% and 0.91% for palm oil, rapeseed, soybean and sunflower oil, respectively (Indexmudi, 2010).

tested sample. His paper has conceptually proven that the ECM[1] model is able to outperform the OLS model when a structural break is considered in the estimation model. Lien (2005) highlights the omission of a structural break that may spuriously estimate the hedging ratio. It is therefore believed that the hedging performance estimations will also be affected. Furthermore, under the Markov switching umbrella, some studies have demonstrated the implications of regime shifts in the spot and futures returns on hedging decisions and performance (see Alizadeh and Nomikos, 2004; Lee et al., 2006; Lee and Yoder, 2007a; Lee and Yoder, 2007b; Lien and Yang, 2010 and Chen and Tsay, 2011). Alexander et al. (2011) on the other hand, illustrate the importance of regime shifts in modelling the option hedging performances. The regime shift model tends to generate different hedging ratios and performances (Lien and Yang, 2010).

More recent literature provides a deeper discussion on regime shift effect on hedging funds performances (Edelman, Fung, Hsieh and Naik, 2012 and Meligkotsidou and Vrontos, 2012) and some relates the shift with spillover transmission on the hedging performance estimation (see Salisu and Mobolaji, 2013; Lau and Bilgin, 2013). Meligkotsidou and Vrontos (2012) infer that regime shifts do effect the correlation and covariance structure of the tested funds. The shifts also influence the hedge funds alpha and beta estimation structure (Edelman et al., 2012). Additionally, the spillover-regime shift model able to improve the hedging performance results (Salisu and Mobolaji, 2013) but not for Lau and Bilgin (2013). Overall, the evidence strongly supports the superiority of the regime shift model in giving a greater risk reduction compared to the conventional model. Based on these findings, we can safely assume that a regime shift does matter in modelling the hedging performance.

This research therefore attempts to investigate the effect of a regime shift on the hedging decision process within the BEKK estimation model in the crude palm oil (CPO henceforth) market. Our investigation differs from the existing regime shift studies as the actual regime shifts experienced in both first and second moments tested series were used. The study applies the Bai and Perron (1998, 2003) procedure (henceforth BP) to identify the regime shift's number and dates, for the mean return series and the Adjusted Inclan and Tiao Iteration cumulative sum of squared algorithm procedure (Sanso et al., 2004) (henceforth AIT ICSS) for the series variance. Within the BEKK framework, the research further postulates the seriousness of the non-inclusion of the shift in risk minimization performance evaluation vis-à-vis the regime shift model.

This research contributes to the existing literature in a number of ways. Firstly, the research may shed some light on the regime shift effect in an emerging commodity market, as previous researchers were more focused on the issue of structural breaks with applications on macroeconomics and financial series in more advanced markets. Secondly, there has been considerable investigation of the issue of structural changes in macroeconomic variables while less attention has been given by preceding researchers to agricultural commodity returns. We assume that the structural changes in the agricultural returns may not be similar to the structural changes in macroeconomic variables. It is because agriculture is more prone to shocks caused by crop production levels which may be influenced by the weather or the crops' biological cycle effects. Thirdly, the identification of shifts in the unconditional mean and variance of the returns series suggests that these breaks need to be incorporated in the model specification to provide a more precise persistency estimation. Precise persistency estimation may enhance the accuracy of estimating the hedging proportion that need to be hedged by CPO market participants and assist them in their rebalancing decision. Further, this research attempts to associate the regime shift effect on the risk reduction performance results. The study tests the effect of regime shift in both the mean and variance series although Lien and Yang (2010) it only focused on the effect of breaks in testing the variance series for long memory hedging strategy performance.

The rest of the paper is structured as follows. Section 1 defines the data used in this analysis. Section 2 explains the basic test procedures and BEKK estimation models. Section 3 discusses the analysis and preliminary findings and the final section concludes.

1. Data

Daily settlement prices of Malaysian crude palm oil and crude palm oil futures (henceforth FCPO) were used over the period of 2nd January 1996 to 15th August 2008. The entire period was used for in-sampling forecasting analysis, while the out-sample estimation process consisted of data spanning from 2nd January 1997 to 30th June 2008, while the period from 2nd January 2008 to 15th August 2008 was reserved for out-sample forecasting analysis. The forecasting periods of 1, 10, 15 and 20 days ahead were done to measure the hedging strategy within in-sample and out-sample estimation models. The CPO settlement prices were gathered from the Bloomberg database and FCPO settlement prices were based on Bursa Malaysia Derivative Berhad.

[1] ECM refers to error correction model.

Figures 1 and 2 plot the CPO and FCPO daily settlement prices and returns within the sampling period. Figure 1 presents both CPO and FCPO prices for the period between January 1996 and August 2008. Both price series tend to establish a stable fluctuation throughout most of the sampling period except for during the Asian Financial Crisis (1997 to 1999) and Mortgage Subprime Crisis (2007 to 2008). These extreme fluctuations may additionally be due to the production pressure during these crisis periods.

The CPO plots in Figure 2 register some regime shifts in its return volatility located around 2001 and 2002 and when it reached its peak in 2007. As for the FCPO, it shows a more stable fluctuation and the plots indicate one possible regime movement in 2001. Interestingly, the Asian Financial Crisis did not have any strong pressure on both spot and futures markets. Much severe volatility was registered during the 9/11 terrorist attack and the US mortgage subprime crisis.

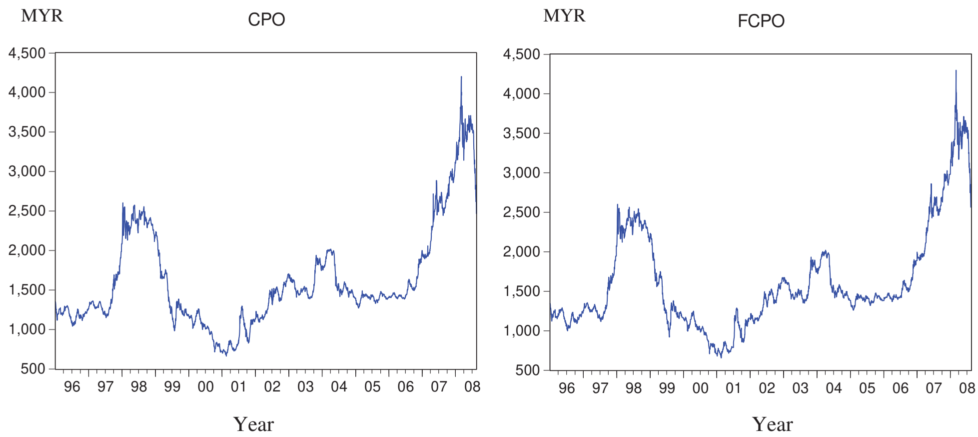

Fig. 1. Plot for CPO and FCPO prices

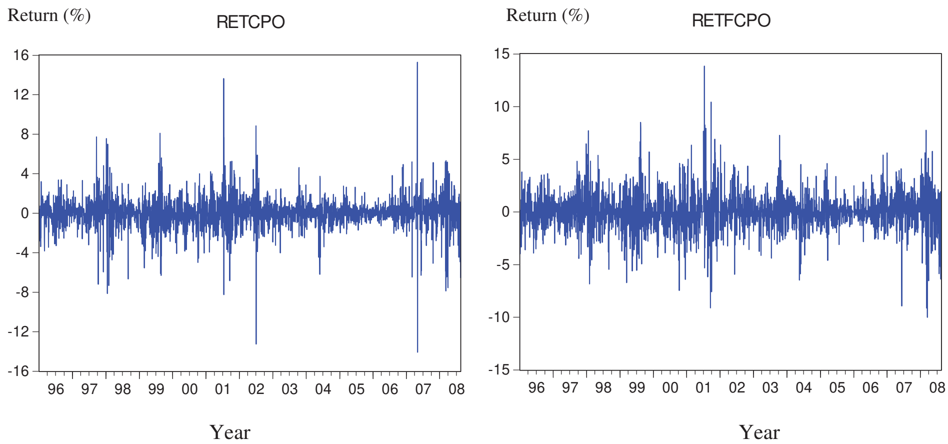

Fig. 2. Plot for CPO and FCPO returns

2. Methodology

The daily settlement CPO and FCPO prices were transformed into returns series using the natural log procedure using the return equation is as below:

$$r_t = ln(p_t / p_{t-1}) \times 100, \quad (1)$$

where r_t represents return of CPO or FCPO at period t. p_t represents the series prices at period t and p_{t-1} denotes the prices at period t-1. Respectively, to test the presence of structural breaks moments, the BP (1998, 2003) and AIT-ICSS techniques are used for the generated unconditional first and second moments, respectively. In the presence of regime shifts in these unconditional first and second moments, we proceed to model the relevant shifts within the BEKK model. Then, the BEKK with and without break estimation models are compared (within in-sample and out-sample period). Using these estimation models, we continue to forecast the minimum variance hedging ratios and see the relevancy of modelling regime shifts on risk minimization measurement results.

2.1. Regime shift identification procedures. *2.1.1. Mean – Bai and Perron test (1998, 2003).* This research considers the BP (1998, 2003) procedure for regime shift identification in the first moment of both series. Bai and Perron (1998) suggest the linear model with m breaks (or m + 1 regimes) as follows:

$$y_t = x_t^{'}\beta + z_t^{'}\delta_j + u_t, \; t = T_{j-1}+1,....,T_j, \quad (2)$$

as $j = 1,...,m+1,$

where y_t denotes the dependent variable at period t, while x_t and z_t are vectors of covariates with dimension (p × 1) and (q x 1), respectively. Note that β and δ_j are the corresponding beta coefficients for x_t and z_t, respectively. Here, u_t represents the residuals at period t. The break points are treated as unknown with the convention that T_0 = 0 and T_{m+1} = T are being used.

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

$$R_t = \alpha + D_j, \tag{3}$$

where R_t represents the series return and α is the mean intercept. Here, D_j represents the dummy variable that accounts for the regime shift in mean for tested series returns (D_j = 1 for t > Regime shift date and zero otherwise).

2.1.2. Variance-adjusted IT-ICSS. Inclan and Tiao (1994) introduced the Iteration cumulative sum of squared algorithm procedure to identify the possible regime shifts located in unconditional variance series. The IT ICSS test is likely to be less appropriate since the test assumes the unconditional variance distributions to be independent and Gaussian distributed. Therefore, Sanso et al. (2004) introduced the AIT ICSS test that is able to address the fat tails and persistency problem in those series. The adjusted statistic encompasses:

$$AIT = \sup_k \left| T^{-1/2} G_k \right|, \tag{4}$$

where $G_k = \hat{\omega}_4^{1/2} (C_k - \frac{k}{T} C_T).$ (5)

The *AIT* test is able to solve both problems by clearly imposing the conditional heteroscedasticity and the disturbance's fourth moment properties via non-parametric adjustment based on the Bartlett kernel. Refer to equation (6), $\hat{\omega}_4$ is a consistent estimator of ω_4 and the non-parametric estimator of ω_4 is defined as follows:

$$\hat{\omega}_4 = \frac{1}{T} \sum_{t=1}^{T} (\varepsilon_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T} \sum_{l=1}^{m} \omega(l,m) \sum_{t-1}^{T} (\varepsilon_t^2 - \hat{\sigma}^2)(\varepsilon_{t-1}^2 - \hat{\sigma}^2), \tag{6}$$

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

2.2. Econometric estimation model. We used a similar mean specification adopted by Ford, Pok and Poshakwale (2005). The model defines as follows:

$$r_{st} = \alpha_s + \varepsilon_{st};\ \varepsilon_{st} \big| \Omega_{t-1} \sim N(0, H_t), \tag{7}$$

$$r_{ft} = \alpha_f + \varepsilon_{ft};\ \varepsilon_{ft} \big| \Omega_{t-1} \sim N(0, H_t), \tag{8}$$

where r_{st} and r_{ft} are returns for spot and futures, Ω_{t-1} defines as the past information at period t-1, where u is constant and ε is residual series. While, for the second moment estimation process, we select the BEKK model developed by Engle and Kroner (1995) which allows capturing the behavior of conditional variance and covariance in two variables simultaneously. The model is said to be able to maintain the positive definiteness of the estimated parameters, where positive definite parameter is essential for the risk estimation process. A negative parameter may lead to a misleading risk estimation result. The BEKK without Regime shift is defined as follows:

$$H_t = C^{*\prime} C^{*} + \sum_{k=1}^{K} G_k^{*\prime} \varepsilon_{t-1} \varepsilon_{t-1}^{\prime} G_k^{*} + \sum_{k=1}^{K} A_k^{*\prime} H_{t-1} A_k^{*}, \tag{9}$$

where H_t is the conditional variance and covariance matrices. While, C^*, A_k^* and G_k^* are $N \times N$ matrices but C^* is the upper triangular and K is the summation limit which determines the model generality and K is assumed to be 1. Since the positive definite parameter estimation for this model is ensured, we would consider applying this model to capture the volatile behaviors between CPO and FCPO returns series.

Next, if there is any break detected for series in the previous regime shift identification test results, subsequently we proceed to modify the BEKK model with regime shift. The model is presented as follows:

$$Y_t = \alpha_0 + \alpha_1 MD_t + \varepsilon_t,\ \varepsilon_t \,|\, \Omega_{t-1} \sim N(0, H_t), \tag{10}$$

$$H_t = C^{*\prime} C^{*} + \sum_{k=1}^{K} G_k^{*\prime} \varepsilon_{t-1} \varepsilon_{t-1}^{\prime} G_k^{*} + \sum_{k=1}^{K} A_k^{*\prime} H_{t-1} A_k^{*} + \sum_{k=1}^{K} C1_k^{*\prime} D1_t C1_k^{*}, \tag{11}$$

where MD_t is a dummy shift in the mean equation, while, $D1_t$ is equal to 1 if $t > k$ and zero otherwise, k equals the date of the shift in the unconditional mean (base on shifts date given in BP tests) while $D1_t$ refers to dummy variables in variance (the regime shift date will be based on *AIT ICSS* test results). $C1$ is a $N \times N$ matrices that represents the coefficient for dummy variables for regime shifts (if any).

2.3. Hedging performance. The minimum variance paradigm (Ederington, 1979) measures hedging effectiveness by computing the risk reduction achieved for hedger's vis-à-vis to the unhedged portfolio. Variance in both spot and futures markets as a proxy for both unhedged and hedged portfolio. The unhedged portfolio can be computed as follows:

$$VAR\left(UH\right) = X_s{}^2 \sigma_s{}^2, \tag{12}$$

where $VAR(UH)$ represents the variance for unhedged portfolio and σ_s^2 denotes variance for spot return. While the variance for hedged portfolio follows the rule presented below:

$$VAR\left(H\right) = \sigma_s{}^2 + h^2 \sigma_f{}^2 - 2h\sigma_{sf}, \tag{13}$$

where $VAR(H)$ refers to variance for hedge position, σ_f^2 represents the variance for futures return and σ_{sf} is covariance between spot and futures returns. And h represents the optimal futures contracts held against the spot contracts (also known as hedging ratio or minimum variance hedging ratio). Since the hedging ratio that represents the hedging decision is governed by the surrounding information, so the hedging ratio is computed based on $\left(\frac{\sigma_{sf} \left| \Omega_{t-1} \right.}{\sigma_f^2 \left| \Omega_{t-1} \right.} \right)$ and the variance for hedging decision turn to $\sigma_s{}^2 \left| \Omega_{t-1} \right. + h^2 \sigma_f{}^2 \left| \Omega_{t-1} \right. - 2h\sigma_{sf} \left| \Omega_{t-1} \right.$ (all σ_s^2, σ_f^2 and σ_{sf} generated from BEKK with and BEKK without break models). Thereafter, the hedging effectiveness can be computed as follows:

$$HE = \frac{VAR(UNH) - VAR(H)}{VAR(UNH)}. \tag{14}$$

3. Empirical results and discussion

Based on the diagnostic tests results[1], it clearly portrays the non-normality features and the presence of both serial correlation and ARCH effect in both series. Generally, it verifies the salient surrounding information which needs to be considered in modeling both mean and volatility returns.

Table 1. BAI and PERRON test results

Specifications						
$zt = \{1\}$	$q = 1$	$p = 0$	$h = 164$	$M = 5$	$\varepsilon = 0.05$	
Tests CPO						
Sup$F_T(1)$	Sup$F_T(2)$	Sup$F_T(3)$	Sup$F_T(4)$	Sup$F_T(5)$	*UDmax*	*WDmax*
3.9760	9.1476**	5.8430	5.8125	6.2259	9.1476*	9.322*
SupF(2l1)	SupF(3l2)	SupF(4l3)	SupF(5l4)			
10.0667*	3.7193	3.2390	2.9660			
Number of breaks selected			Structural breaks date			
Sequential:	0			SB 1:	09/11/1998 (744)	
LWZ:	0			SB 2:	28/07/1999 (931)	
BIC:	0					
Tests FCPO						
Sup$F_T(1)$	Sup$F_T(2)$	Sup$F_T(3)$	Sup$F_T(4)$	Sup$F_T(5)$	*UDmax*	*WDmax*
4.2273	8.8389**	7.5893*	5.8110	6.7800**	8.8389*	9.0074
SupF(2l1)	SupF(3l2)	SupF(4l3)	SupF(5l4)			
9.7387**	3.9313	2.4722	2.4722			
Number of breaks selected			Structural breaks date			
Sequential:	0			SB 1:	01/12/1998 (760)	
LWZ:	0			SB 2:	30/07/1999 (933)	
BIC:	0					

Notes: 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).

The evidence of regime shifts in both series mean is presented in Table 1. The results infer that the mean for CPO has undergone two regime shifts dated 9 November 1998 and 28th July 1999. However, a similar result is validated for FCPO and the mean experienced some structural changes on 1st December 1998 and 30th July 1999. In summary, we can see a similar break reported for both series since CPO and FPCO prices moved concurrently. Obviously, the breaks that were detected during and ex-post Asian financial crisis periods occurred when the Malaysian government put in place capital control measures to strengthen the financial market. In the palm oil industry, both years experienced a volatile period due to the uncontrolled soaring production during those periods.

[1] The study adopted three types of unit root tests including the Augmented Dickey Filler (ADF henceforth) test, Phillip-Perron (PP henceforth) test and Kwiatkowski, Philips, Schmidt, and Shin (KPSS henceforth) test. Subsequently, the Ljung-Box test and correlograms of squared residual were done to test the existence of serial correlation and ARCH effect in the tested series. Due to space constraints, we are not able to include the details of the diagnostic test results in this paper.

Table 2. AIT ICSS tests results

	No of regime shift	ICSS(k_2)		Local events	Events
CPO	Nil	Nil			
FCPO	4	31/10/1996	(217)	High level of CPO production	Pre Asian Financial Crisis
		02/07/2001	(1434)	Low biological cycle for palm tree	
		02/10/2001	(1500)	Low biological cycle for palm tree	Post Terrorist Attack in US
		18/03/2008	(3185)	Strong demand for CPO	Mortgage Subprime & Food Crisis
				Low level of CPO production	

The results for *AIT ICSS* procedure are summarized in Table 2. Based on the *AIT ICSS* results, the test has failed to prove any breaks present in the CPO unconditional variance. However, there are four breaks reported for FCPO variance in October 1996, July and October 2001 and March 2008.

Based on the findings, the first break evidently occurred prior to the Asian Financial Crisis. Locally, the volatility during this period might be due to a generous growth in production that was a result of a good biological cycle for the commodity. Another two breaks were registered in July and October 2001, prior to and after the terrorist attack in the US. However, the structural change in the variance CPO return is not directly affected by this event. The attack had an almost instantaneous effect on the US stock markets and the global stock markets volatility. This CPO series variance changes tend to be influenced by domestic forces, which consist of CPO production shortage (lower biological cycle) more than this terrorist attack. In addition, the intense competition with other vegetable oil (soy oil, rapeseed oil and sunflower oil) producers with their increased production might have resulted in the increased volatility of the CPO market that particular year.

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 Subprime Crisis in early 2007. The global recession has caused countries to implement measures to strengthen their liquidity and financial infrastructure. This pressure was further translated into a downward trend in the oil and commodity prices, including CPO. In addition, the level of CPO production was very promising along with the great support from the increasing world demand for such oil during that period. In addition, a weak production by other vegetable oil producers was believed to have further strengthened the CPO prices. Nevertheless, the current global turmoil has heightened the uncertainty in the movement of the CPO prices, which has over-shadowed the strong CPO demand forces.

3.1. Persistency estimation results. To examine the seriousness of omitting structural breaks in mean and variance estimation model, we further estimated mean and variance for both series using two separate BEKK models (BEKK-GARCH and BEKK-GARCH RS). The maximum likelihood parameters estimation results for both models are presented in Appendix A.

Table 3. BEKK-GARCH and BEKK-GARCH SB persistency estimation results

	BEKK-GARCH			
	*A**	*G**	*A*+G**	Log likelihood
CPO	0.005	0.95	0.955	-10744
FCPO	0.285	0.866	1.151	
	BEKK-GARCH SB			
	*A**	*G**	*A*+G**	Log likelihood
CPO	0.15	0.93	1.08	-10752
FCPO	0.005	0.93	0.935	

Overwhelming evidence supports the accuracy of volatility persistency parameters estimation when we ignore the existence of structural breaks either in mean or variance (ranging from Deibold, 1986 to Fang and Miller, 2008). Using the BEKK-GARCH and BEKK-GARCH SB estimation model, we found a downsize bias in FCPO volatility parameters (the variance persistency parameter reduced from 1.15 to 0.93 (see Table 3). Similar results using a basic ARCH and GARCH frameworks were documented in Lamoureux and Lastrapes (1990), and Fang and Miller (2008). In contrast, when structural break is included in CPO mean specification, the BEKK estimates merely a higher persistence than the non break model (similar results reported in Morana and Beltratti, 2004). Intuitively, we strongly conclude that potential regime shift is one of the important aspects in volatility clustering estimation process. The breaks will influence the non biasness in volatility estimation parameters.

3.2. Hedging performance analysis. Table 4 below presents variance results.

Table 4. Minimum variance results

	BEKK-GARCH				BEKK-GARCH RS			
	Hedge ratio	Var(UH)	Var(H)	Min reduction (%)	Hedge ratio	Var(UH)	Var(H)	Min reduction (%)
	In-sample				In-sample			
Forecasting day ahead								
1	0.53	1.64	1.01	38.47%	0.41	2.45	1.74	29.17%
10	0.47	2.33	1.83	21.27%	0.44	1.83	1.12	39.10%
15	0.41	2.46	2.06	16.05%	0.45	1.64	1.01	38.51%
20	1.01	2.88	-0.08	102.77%	0.24	5.43	4.81	11.34%
	Hedge ratio	Var(UH)	Var(H)	Min reduction (%)	Hedge ratio	Var(UH)	Var(H)	Min reduction (%)
	Out-sample				Out-sample			
Forecasting day ahead								
1	0.5	1.47	0.88	40.32%	0.47	1.95	1.19	38.92%
10	0.56	3.64	2.66	27.10%	0.48	3.28	2.42	26.28%
15	0.54	2.96	2.07	29.92%	0.47	2.67	1.89	29.09%
20	0.53	2.11	1.34	36.73%	0.46	2.08	1.40	32.78%

Based on Table 4 findings, we can understand that the BEKK-GARCH RS model estimated a consistent range of hedging ratio (within 41% and 45% hedging position against the CPO contract) and achieved between 29% to 39% risk reduction from the participant's total price risk exposure (refer to 1, 10 and 15 forecasting days ahead). Additionally, participants need to hedge all of their spot positions and get a maximum risk reduction of 100% during the 20-day forecasting period ahead. However, when we considered the regime shift in the BEKK estimation model, the results showed that investors only hedged 24% of their spot position and obtained much lower risk reduction than in the non-break model.

Based on the out-sample analysis, similar results were found in both models, where the BEKK-GARCH RS 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-GARCH RS model and 37% for the other BEKK model. However, the smallest variance reduction was attained at an average of 25% during the 10-day forecasting period ahead for both models. The risk reduction results for 1-day and 10-day forecasting periods ahead imply that hedgers achieved 38% on the first day forecasting period ahead than the 25% attained on the 10-day forecasting period ahead. Such evidence portrays that hedging performance changes over time since hedgers tend to revise their hedging proportion in respond to the surrounding information flow into the CPO market. In contrast to the out-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.

In practice, hedges need to rebalance their hedging proportion whenever there are changes in the hedging ratio. Hedgers, however, need to consider the economical results, such as whether the rebalancing exercise gives an economically feasible result. In this study, we assume the hedger seeks risk minimization where each rebalancing decision is based on whether the rebalancing can maintain the risk minimization objective. Based on the general BEKK model, hedgers need to revise their hedging proportion twice, where they need to hedge 53% during the 1-day and rebalance the hedging proportion to 47% in 10-day forecasting period ahead. In addition, they should also hedge 41% of their CPO positions in 15-day and rebalance it to 100% of their CPO in 20-day forecasting period ahead. The two-time rebalancing decision generated risk minimization results that were extremely different. With the regime shift model, however, hedges only need to rebalance their hedging position once from 45% in 15-day to 24% in 20-day forecasting period ahead acquiring 11% to 38% risk minimization result.

Overall, the BEKK-RS model unfailingly portrayed a more consistent range of hedging ratio and risk reduction for both the in-sample or out-sample forecasting procedure compared to the non-RS model. We can generally infer a similar range of hedging proportions against the spot contract in the 1, 10, and 15 forecasting period ahead and required less rebalancing activities by CPO hedges. However, the general BEKK model exhibits inconsistency and a wider range of in-sample hedging ratio vis-à-vis the out-sample one and resulted more frequent rebalancing activities for CPO hedgers. In terms of hedging performance, none of the forecasting periods ahead drives the same trend of variance reduction in either the BEKK-GARCH or BEKK-GARCH RS model.

Based on the above findings, we infer that the regime shift is vital in modelling the volatility clustering estimation process as the shift model generated different sets of variance-covariance parameters and estimated a more consistent hedging ratio results than the non-RS model. Hence, the consistency of the hedging ratio would 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-RS model in almost all the cases. As such, without the regime shift the hedging performance tends to be an upward bias and produces an extreme range of hedging ratio. Consequently, the non-inclusion of regime changes 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 less accurate proportion that needs to be hedged against the spot contract and fallaciously evaluate the strategic rebalancing decisions and performances.

Concluding remarks

The econometric model introduced in this study demonstrates the non-trivial effect of regime changes into minimum variance hedging ratio and risk minimization analysis in the Malaysian CPO and FCPO markets. From an academic perspective, this study may shed some light on hedging effectiveness measurement that caters for the regime shift effect. From the practitioner perspective, the study provides information on accurate hedging proportion measurement and relates it to hedgers rebalancing activities in CPO market.

Our analysis acknowledges the presence of regime shifts in the series mean (using BP procedure) and variance (using *AIT ICSS* procedure) in both series. Using a parsimony BEKK model, the study further displays the consequences of omitting these shifts in the hedging performance context. The research proceeded to test the significance of the effect of breaks on the hedging ratio and hedging performance accuracy. The results show that ignoring the regime shifts in volatility clustering modelling will generate bias persistency coefficient estimation and misleading hedging ratio, further affect the market participant's hedging rebalancing decision. Based on the risk minimization results for both models, the findings validated the tendency of the BEKK-GARCH RS to estimate a steadier hedging ratio and hedging performance. However, a more volatile hedging ratio and hedging performance was reported for the non-RS model (refer to in-sample analysis).

In conclusion, this research highlights the importance of regime shifts in estimating a more precise minimum variance hedging ratio and hedging performance in CPO market. Using the similar BEKK-GARCH RS method, future research could enhance the present regime shift hedging performance investigations using other flourishing and emerging commodities markets such as India and China.

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Appendix A. Maximum likelihood estimation

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:

$$H_t = C^{*\prime} C^* + \sum_{k=1}^{K} G_k^{*\prime} \varepsilon_{t-1} \varepsilon_{t-1}^{\prime} G_k^* + \sum_{k=1}^{K} A_k^{*\prime} H_{t-1} A_k^*.$$

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:

$$H_t = C^{*\prime}C^{*} + \sum_{k=1}^{K} G_k^{*\prime}\varepsilon_{t-1}\varepsilon_{t-1}^{\prime}G_k^{*} + \sum_{k=1}^{K} A_k^{*\prime}H_{t-1}A_k^{*} + \sum_{k=1}^{K} C1_k^{*\prime}D1_t C1_k^{*} + \sum_{k=1}^{K} C2_k^{*\prime}D2_t C2_k^{*} + \sum_{k=1}^{K} C3_k^{*\prime}D3_t C3_k^{*} + \sum_{k=1}^{K} C4_k^{*\prime}D4_t C4_k^{*},$$

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.

Table 5. Maximum likelihood estimation for BEKK-GARCH and BEKK-GARCH RS

Coefficient	BEKK-GARCH	BEKK-GARCH RS	Coefficient	BEKK-GARCH	BEKK-GARCH RS	Coefficient	BEKK-GARCH	BEKK-GARCH RS
$\alpha_0 s$	-0.020481	-0.119361	C4f		0.48649	Q(1)s	50.662	34.39
	[0.41595]	[0.00000]			[0.00732]		[0.0000]	[0.0000]
$\alpha_0 f$	-0.002272	-0.0792	As	-0.28932	0.32757	Q(5)s	86.844	64.752
	[0.93192]	[0.00024]		[0.42202]	[0.57343]		[0.0000]	[0.0000]
$\alpha_1 s$		0.09261	Asf	-1.01909	1.10778	Q(10)s	134.905	107.097
		[0.00000]		[0.00000]	[0.00000]		[0.0000]	[0.0000]
$\alpha_1 f$		0.05591	Afs	-0.68887	0.63655	Q(1)f	1.021	0.754
		[0.00956]		[0.00509]	[0.10279]		[0.3120]	[0.385]
$\alpha_2 s$		0.029	Af	0.08844	-0.14306	Q(5)f	19.52	15.105
		[0.00000]		[0.825425]	[0.80088]		[0.0010]	[0.0010]
$\alpha_2 f$		0.01156	Gs	0.18714	-0.191	Q(10)f	49.413	43.97
		[0.80349]		[0.234838]	[0.33663]		[0.0000]	[0.0000]
Cs	-0.106206	-0.11778	Gsf	-0.42696	0.36523	Q2(1)s	31.109	32.137
	[0.41059]	[0.32218]		[0.00017]	[0.08698]		[0.0000]	[0.0000]
Csf	0.47601	0.44783	Gfs	-0.26063	-0.19356	Q2(5)s	38.34	69.01
	[0.00002]	[0.00486]		[0.00000]	[0.05276]		[0.0000]	[0.0000]
Cf	-0.000032	-0.00162	Gf	-0.10775	-0.29306	Q2(10)s	42.35	75.006
	[0.99979]	[0.99365]		[0.182007]	[0.00282]		[0.0000]	[0.0000]
$C_1 f$		-0.00054				Q2(1)f	2.73	0.409
		[0.99209]	LR	-10744.54774	-10752.35608		[0.1000]	[0.5230]
$C_2 f$		-0.0007				Q2(5)f	6.01	17.863
		[0.99015]					[0.3050]	[0.0030]
$C_3 f$		0.0009				Q2(10)f	13.591	29.841
		[0.99612]					[0.1920]	[0.0010]

Notes: *P*-values are reported in parentheses.