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Palm oil spot-futures relation: Evidence from unrefined and refined products

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Abstract: This study examines the palm oil spot-futures relation in terms of mean and volatility spillovers from 2010 to 2018. Based on the cross-correlation function of standardised residuals and its squared residuals, our results show: first, crude palm oil (CPO) futures returns Granger cause refined palm oil, palm stearin and palm olein spot returns. Second, refined palm kernel oil spot returns Granger cause crude palm kernel oil futures returns in mean and variance. Third, CPO spot and refined palm olein futures returns are independent; and fourth, there is volatility spillover from CPO futures market to refined palm oil spot market within longer time. These findings suggest that refiners can use CPO futures returns instead of crude palm kernel oil futures returns for predicting the future spot return of refined palm oil products. To lock in purchasing price of unrefined palm oil products, the producers can rely on the spot volatility to decide the optimal number of crude palm kernel oil futures contracts.

Keywords: causality in mean; causality in variance; crude palm oil; palm kernel oil; spot-futures relation

Within the large body of literature on commodity spot-futures relation that documents the ability of futures returns in predicting spot returns, mean and volatility spillovers between spot and futures prices are most intriguing. However, there is a lack of study done on commodity-related products. This study intends to validate whether futures prices reflect the market expectation of future spot prices. For example, can futures returns of refined products Granger cause spot returns of unrefined products in mean and variance? If it is true, an efficient futures market can quickly reflect market participants' expectation on future supply and demand.

The refining process breaks both crude palm oil (CPO) and crude palm kernel oil into its constituent products, namely refined, bleached and deodorized (RBD) palm oil, RBD palm stearin, RBD palm olein, and RBD palm kernel oil. However, when the price of a refined palm oil product falls, refiners need to lock in the selling price for the product of which is needed to be delivered in the future. Hence, they need to hedge in the RBD palm oil olein futures market.

There is yet to be a study done on the lead-lag relationship between spot and futures prices of refined and unrefined palm oil products. Most of studies on the price relationship are found to focus on oil products (Asche et al. 2003; Choi and Hammoudeh 2009; Ji and Fan 2011; Mirantes et al. 2012; Nakajima and Hamori 2012; Liu and Ma 2014). Hence, our study is important to reduce refiners' exposure to market risk that involves unrefined and refined palm oil markets. Thus, the difference between price of unrefined and refined products represents the margin for the refiners.

LITERATURE REVIEW

Under the no-arbitrage condition, the cost-of-carry model is developed to explain the relationship between

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commodity spot and futures prices (Kaldor 1939; Working 1949; Brennan 1958). Besides that, the model can be used in pricing futures contracts. Within the context of the non-arbitrage theory, the futures price should depend on the current spot price and cost of carrying of the underlying goods from now until the date of delivery. However, Brenner and Kroner (1995) state that this theory ignores the efficient market hypothesis.

Since futures markets commonly have lesser restrictive regulation or lower transaction cost, futures prices should respond to new information faster than spot prices. Using error correction and generalized autoregressive conditional heteroskedasticity-in-mean models, Kawamoto and Hamori (2011) demonstrate that West Texas Intermediate (WTI) futures prices are consistently efficient within the 8-month maturity, as well as consistently efficient and unbiased within 2-month maturity. The function of price discovery is detected in commodity futures markets (Mahalik et al. 2014; Ghoddusi 2016). Research on the commodity spot-futures relation for hedging strategies and risk avoidance through the futures markets is of great significance especially during the uncertain periods (Toyoshima et al. 2013; Go and Lau 2014; Go and Lau 2015).

Although a futures contract seems to be a feasible choice to hedge risk, some studies claim that the use of such a contract cannot play the role of price discovery under several conditions (Bhar and Hamori 2005; Alquist and Kilian 2010). Several authors attempt to detect asymmetric adjustment of positive and negative bases in the long-run relationship between WTI spot and futures prices (Liu et al. 2011; Kolodziej and Kaufmann 2013).

Several authors also look into the issue of financial crisis and structural break in their studies (Alzahrani et al.2014; Chen et al. 2014). Meanwhile, Balcilar et al. (2015) use the Markov-switching vector error correction model to capture time-varying casual linkages between daily WTI spot and futures prices up to one, two, three and four months prior to delivery date.

From the perspective of investor demand on copper, Tilton et al. (2011) hypothesise that the existence of investor demand during the period of strong contango tends to cause excess inventories for future production, thereby depressing spot prices. Gulley and Tilton (2014) provide the first empirical evidence based on daily data of 1994–2011. Their finding indicates that the correlation coefficient between changes in copper spot and futures prices is high when the market in strong contango instead of backwardation and weak contango.

Other researchers also test the validity of the hypothesis of investor demand in other metals. However, their findings are less supportive of such a hypothesis. For instance, Fernandez (2015) extends the scope of the study by including traded aluminium, copper, lead, nickel, tin and zinc in the London Metal Exchange during the sample period of 1992–2014. After controlling conditional heteroscedasticity in returns, detecting unconditional mean-return breakpoints, and detecting and removing outlying observations, the author finds that the existence of a weak linkage between spot and futures markets during the contango period. Fernandez (2016) further finds that a strong association between both returns during the period of high stocks (positive interest-adjusted basis means storage cost rate more than convenience yield) leads to the occurrence of causality from futures returns to spot returns regardless of stock levels. In the case of CPO, Go and Lau (2017) extend the hypothesis by taking the variance of the increments in the random walk process into account. Their finding shows that the preference for holding a long position in the futures market is due to the anticipation of insufficient supply during backwardation.

DATA AND METHODOLOGY

Daily data of spot and futures prices from January 4, 2010 to March 30, 2018 for unrefined and refined palm oil products are obtained from Bloomberg and Bursa Malaysia (2018). For unrefined palm oil products, daily crude palm oil spot (*CPO*), crude palm oil futures (*FCPO*) and crude palm kernel oil futures (*FPKO*) prices are used.

The futures contracts for both unrefined products with the maturity length of three months are a reasonable choice because high liquidity of contracts can ensure the efficient price discovery. For refined palm oil products, RBD palm oil spot (*RPO*), RBD palm stearin spot (*RPST*), RBD palm olein spot (*RPOL*), RBD palm kernel oil spot (*RPKO*) and RBD palm olein futures (*FPOL*) prices are used. However, *FPOL* prices for three months of maturity are only available from June 13, 2014 to December 31, 2015. In order to achieve stationarity and reduce the variation of series, these prices are transformed to the first ln-difference of daily return (R_t) at time t by using $R_t = \ln(P_t/P_{t-1}) \times 100$, where P_t is the daily price at time t, P_{t-1} is the daily price at preceding time t and ln stands for natural logarithm.

Table 1 shows the results of augmented Dickey-Fuller unit root tests for the level of daily *CPO*, *FCPO*,

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Table 1. Results of augmented Dickey-Fuller unit root test

	CPO	*FCPO*	*FPKO*	*RPKO*	*RPO*	*RPST*	*RPOL*	*FPOL*
Constant and without time trend (1% critical value = –3.4)								
Test statistic:	–29.147 (0)	–33.358 (0)	–38.159 (0)	–15.897 (3)	–35.38 (0)	–48.676 (0)	–30.282 (1)	–27.586 (0)
p-value				0.000				
Constant and with time trend (1% critical value = –3.9)								
Test statistic:	–29.131 (0)	–33.345 (0)	–38.153 (0)	–15.898 (3)	–35.378 (0)	–48.655 (0)	–30.272 (1)	–27.579 (0)
p-value				0.000				

CPO – daily crude palm oil spot return; *FCPO* – daily crude palm oil futures return; *FPKO* – daily crude palm kernel oil futures return; *RPKO* – daily RBD palm kernel oil spot return; RBD – refined, bleached and deodorized; *RPO* – daily RBD palm oil spot return, *RPST* – daily RBD palm stearin spot return, *RPOL* – daily RBD palm olein spot return and *FPOL* – daily RBD palm olein futures return; optimal lag length of the test is reported in (.); lag length is selected based on the minimum value of Schwarz's information criterion to ensure white noise residuals

Source: authors' own estimation based on data provided by the Bursa Malaysia (2018)

FPKO, *RPKO*, *RPO*, *RPST*, *RPOL* and *FPOL* returns. The test is performed for each series using the model with an intercept and the other model with both intercept and trend. The results show that all returns have the stationary movement at the level form.

Exogenous events contribute to structural change in both mean and variance over time, thereby leading to an asymmetric correlation between spot and futures returns (Ruan et al. 2016). To capture such behaviour, Cheung and Ng (1996) develop the cross-correlation function (CCF) of standardised residuals and squared standardised residuals approach. Such an approach is used to detect the non-linear causal relation in the mean and variance of two stationary series (Henry et al. 2007).

The CCF involves the two-step procedure. The first step is to fit each time series using a univariate model. It is followed by the second step that tests the short-term dynamics between two series since time series are likely to interact with each other. This can be done by testing the null hypothesis of no causality in mean based on the CCF values of standardised residuals, while the value of standardised squared residuals is used for testing the null hypothesis of no causality in variance.

Cheung and Ng (1996) allocate equal weighting to each lag which can be subject to severe size distortions in the presence of causality in mean. Furthermore, the pattern of causality in variance also fails to detect with zero cross-correlation between innovations. To overcome the limitation, Hong (2001) develops the non-uniform weighting cross-correlation through simulation to provide a flexible weighting scheme for cross-correlation at each lag.

Spot and futures returns are assumed to be expressed as Equation 1 and Equation 2.

$$SR_t = \mu_{SR,t} + \sqrt{h_{SR,t}}\,\varepsilon_t \quad (1)$$

$$FR_t = \mu_{FR,t} + \sqrt{h_{FR,t}}\,\xi_t \quad (2)$$

where SR_t and FR_t are the daily spot and futures returns at time t, respectively; $\mu_{SR,t}$ and $\mu_{FR,t}$ are the conditional mean of SR_t and FR_t, respectively; $h_{SR,t}$ and $h_{FR,t}$ are the conditional variance of SR_t and FR_t, respectively; ε_t and ξ_t are two independent white noise processes with zero mean and unit variance.

To test causality in mean, Equation 3 and Equation 4 are used to construct standardised innovations for respective spot and futures returns as both ε_t and ξ_t are unobservable.

$$\varepsilon_t = \frac{SR_t - \mu_{SR,t}}{\sqrt{h_{SR,t}}} \quad (3)$$

$$\xi_t = \frac{FR_t - \mu_{FR,t}}{\sqrt{h_{FR,t}}} \quad (4)$$

Then, the estimated ε_t and ξ_t are used to compute the sample cross-correlation coefficient at lag $k\left(\hat{r}_{\varepsilon,\xi}(k)\right)$ by using Equation 5.

$$\hat{r}_{\varepsilon,\xi}(k) = \frac{C_{\varepsilon,\xi}(k)}{\sqrt{C_{\varepsilon,\varepsilon}(0)\,C_{\xi,\xi}(0)}} \quad (5)$$

where $C_{\varepsilon,\xi}(k)$ is the k^{th} lag sample cross-covariance given by:

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$$C_{\varepsilon,\xi}(k)=\begin{cases}T^{-1}\sum_{t=k+1}^{T}\hat{\varepsilon}_t\,\hat{\xi}_{t-k},\ k\geq 0\\ T^{-1}\sum_{t=-k+1}^{T}\hat{\varepsilon}_{t+k}\,\hat{\xi}_t,\ k<0\end{cases},$$

$C_{\varepsilon,\varepsilon}(0)$ is the sample variance of standardised residuals for spot return, and $C_{\xi,\xi}(0)$ is the sample variance of standardised residuals for futures return.

Under the regularity condition, we can reject the null hypothesis of no causality in mean if the test statistic value based on Equation 6 is greater than the critical value from a chi-square distribution.

$$S_1=T\left[\sum_{i=1}^{k}\left(\hat{r}_{\varepsilon,\xi}(k)\right)^2\right]\xrightarrow{L}\chi^2(k) \tag{6}$$

where $\xrightarrow{L}$ denotes the convergence in the distribution.

When the degree of freedom of k is large, this test statistic is transformed into a standard normal distribution by subtracting the mean of k and dividing by the standard deviation of $(2k)^{1/2}$. As a consequence, the standardised version of S_1 is written as Equation 7.

$$M_1=\frac{S_1-k}{\sqrt{2k}}\xrightarrow{L}N(0,1) \tag{7}$$

The test statistic based on Equation 7 is compared to the upper-tailed critical value of a standard normal distribution. If the test statistic is greater than the critical value, then we reject the null hypothesis of no causality in mean.

To test causality in variance, Equation 8–9 are used to construct the square of the standardised innovations for respective spot and futures returns as both u_t and v_t are unobservable.

$$u_t=\frac{\left(SR_t-\mu_{SR,t}\right)^2}{h_{SR,t}} \tag{8}$$

$$v_t=\frac{\left(FR_t-\mu_{FR,t}\right)^2}{h_{FR,t}} \tag{9}$$

Then, the estimated u_t and v_t are used to compute the sample cross-correlation coefficient at lag $k\left(\hat{r}_{u,v}(k)\right)$ by using Equation 10.

$$\hat{r}_{u,v}(k)=\frac{C_{u,v}(k)}{\sqrt{C_{u,u}(0)\,C_{v,v}(0)}} \tag{10}$$

where $C_{uv}(k)$ is the k^{th} lag sample cross-covariance given by:

$$C_{u,v}(k)=\begin{cases}T^{-1}\sum_{t=k+1}^{T}\hat{u}_t\,\hat{v}_{t-k},\ k\geq 0\\ T^{-1}\sum_{t=-k+1}^{T}\hat{u}_{t+k}\,\hat{v}_t,\ k<0\end{cases},$$

$C_{u,u}(0)$ is the sample variance of squared standardised residuals for spot return, and $C_{v,v}(0)$ is the sample variance of squared standardised residuals for futures return.

Under the regularity condition, we can reject the null hypothesis of no causality in variance if the test statistic value based on Equation 11 is greater than the critical value from a chi-square distribution.

$$S_2=T\left[\sum_{i=1}^{k}\left(\hat{r}_{u,v}(k)\right)^2\right]\xrightarrow{L}\chi^2(k) \tag{11}$$

As stated above, when the degree of freedom of k is large, Equation 11 is transformed into a standard normal distribution by subtracting the mean of k and dividing by standard deviation of $(2k)^{1/2}$. The standardised version of S_2 is written as Equation 12.

$$M_2=\frac{S_2-k}{\sqrt{2k}}\xrightarrow{L}N(0,1) \tag{12}$$

If the test statistic based on Equation 12 is greater than the critical value from a normal distribution, then we can reject the null hypothesis of no causality in variance.

RESULTS

Based on correlogram and Schwarz's information criterion, return series are modelled by using a different type of GARCH specifications. To ensure the non-negativity of the conditional variance, an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) (1, 1) model is used for *CPO*, *RPKO* and *FPOL*. As shown in Table 2, the coefficients of ARCH and GARCH terms in these selected models significantly capture the asymmetric effect caused by positive and negative shocks.

To comply with the principle of parsimony modelling, the standard autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) frameworks are selected for the following returns. As shown in Table 2, ARMA (1, 1) – ARCH (1) and AR (1) – ARCH (1) models are selected for *FPKO* and *RPO*, respectively (ARMA stands for autoregressive moving average;

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Table 2. Estimation results of univariate models

Estimation results of univariate ARMA – exponential GARCH (EGARCH) models[a]

	CPO		*RPKO*		*FPOL*	
	ARMA (1, 1) – EGARCH (1, 1)		ARMA (2, 3) – EGARCH (1, 1)		ARMA (2, 4) – EGARCH (1, 1)	
	estimate	standard error	estimate	standard error	estimate	standard error
Conditional mean equation						
a_0	–0.0003	0.0004	–0.0005	0.0003	2.03×10^{-6}	0.0003
a_1	0.2901	0.498	–0.2592***	0.0805	1.727***	0.0985
a_2	–	–	0.7288***	0.0798	0.1368	0.1721
b_1	–0.2626	0.5044	0.1891**	0.0817	–0.0027	907.7236
b_2	–	–	–0.6465***	0.0863	–89.3148***	4.1402
b_3	–	–	0.1542***	0.028	2.87	8.6299
b_4	–	–	–	–	6.7745***	1.4754
Conditional variance equation						
w	–0.2263	0.1539	–1.0764***	0.1661	–14.7312***	0.441
α_1	0.0879***	0.0316	0.4742***	0.0443	0.0631***	0.0078
γ_1	–0.0298*	0.0163	–0.0573**	0.0286	0.2182***	0.0065
β_1	0.9813***	0.0163	0.9067***	0.02	0.1801***	0.0249
Volatility persistence	0.9813		0.9067		0.1801	
Log-likelihood	2 551.323		3 609.985		6 497.681	
SIC	–5.6915		–4.9004		–14.5755	
$Q(20)$	26.161 (0.126)		20.236 (0.262)		56.226 (0.000)	
$Q^2(20)$	12.328 (0.904)		21.229 (0.384)		2.3031 (1.000)	
ARCH-LM	1.2326 (0.2669)		1.4938 (0.2216)		0.2769 (0.5987)	

Estimation results of univariate ARMA – ARCH models[b]

	FPKO		*RPO*	
	ARMA (1, 1) – ARCH (1)		AR (1) – ARCH (1)	
	estimate	standard error	estimate	standard error
Conditional mean equation				
a_0	0.0002	0.2055	-8.6×10^{-20}	0.0003
a_1	0.0066	906.8128	1.24×10^{-17}	0.0016
b_1	–0.0027	907.7236	–	–
Conditional variance equation				
w	0.001***	2.51×10^{-5}	0.0004***	3.98×10^{-5}
α_1	0.1228*	0.0714	0.5349***	0.1404
Volatility persistence	0.1228		0.5349	
Log-likelihood	2 957.936		3 123.654	
SIC	–4.0275		–5.1508	
$Q(20)$	16.068 (0.653)		4.9491 (1.000)	
$Q^2(20)$	13.003 (0.877)		0.0252 (1.000)	
ARCH-LM	0.5607 (0.454)		0.0008 (0.978)	

Estimation results of univariate ARMA-GARCH models[c]

	FCPO		*RPOL*		*RPST*	
	ARMA (1, 1) – GARCH (1, 1)		ARMA (1, 1) – GARCH (1, 1)		ARMA (2, 1) – GARCH (7, 1)	
	estimate	standard error	estimate	standard error	estimate	standard error
Conditional mean equation						
a_0	2.35×10^{-5}	0.0004	–0.0003	0.0003	–0.0002	0.0007
a_1	0.0893	0.8427	0.1485	0.0911	–0.9094	0.5359
a_2	–	–	–	–	–0.1654	0.1084
b_1	–0.0559	0.8451	–0.4108***	0.0821	0.6882	0.5392

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Continuation Table 2

Estimation results of univariate ARMA-GARCH models[c]	*FCPO*		*RPOL*		*RPST*	
	ARMA (1, 1) – GARCH (1, 1)		ARMA (1, 1) – GARCH (1, 1)		ARMA (2, 1) – GARCH (7, 1)	
	estimate	standard error	estimate	standard error	estimate	standard error
Conditional variance equation						
w	3.5×10^{-5}**	1.5×10^{-5}	0.0003***	5.57×10^{-5}	7.90×10^{-5}***	1.29×10^{-5}
α_1	0.0563***	0.0196	0.2919***	0.0711	0.3351***	0.0712
β_1	0.8246***	0.06	0.196*	0.1153	0.1716*	0.1016
β_2	–	–	–	–	–0.1129*	0.065
β_3	–	–	–	–	0.0610	0.0566
β_4	–	–	–	–	0.1387	0.0941
β_5	–	–	–	–	0.072	0.1161
β_6	–	–	–	–	0.0157	0.091
β_7	–	–	–	–	0.1812**	0.0811
Volatility persistence	0.881		0.4879		0.5272	
Log-likelihood	3 227.225		2 880.73		3 020.003	
SIC	–5.3108		–4.7361		–4.93	
$Q(20)$	22.196 (0.275)		17.858 (0.532)		21.687 (0.300)	
$Q^2(20)$	14.526 (0.803)		17.616 (0.613)		26.964 (0.136)	
ARCH-LM	0.0333 (0.8551)		0.1135 (0.7362)		0.2084 (0.6481)	

[a] $$R_t = \alpha_0 + \sum_{i=1}^{P_1} a_i R_{t-i} + \sum_{i=1}^{P_2} b_i \varepsilon_{t-i} + \varepsilon_t,\ \varepsilon_t = z_t\sqrt{h_t},\ \varepsilon_t \sim GED\left(0, h_t\right)$$

$$\ln h_t = w + \alpha_1\left(\left|\varepsilon_{t-1}\right| \Big/ \sqrt{h_{t-1}}\right) + \gamma_1\left(\varepsilon_{t-1} \Big/ \sqrt{h_{t-1}}\right) + \beta_1 \ln h_{t-1}$$

[b] $$R_t = \alpha_0 + \sum_{i=1}^{P_1} a_i R_{t-i} + \sum_{i=1}^{P_2} b_i \varepsilon_{t-i} + \varepsilon_t,\ \varepsilon_t = z_t\sqrt{h_t},\ \varepsilon_t \sim GED\left(0, h_t\right)$$

$$h_t = w + \sum_{i=1}^{P_3} \alpha_i \varepsilon_{t-i}^2$$

[c] $$R_t = \alpha_0 + \sum_{i=1}^{P_1} a_i R_{t-i} + \sum_{i=1}^{P_2} b_i \varepsilon_{t-i} + \varepsilon_t,\ \varepsilon_t = z_t\sqrt{h_t},\ \varepsilon_t \sim GED\left(0, h_t\right)$$

$$h_t = w + \sum_{i=1}^{P_3} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{P_4} \beta_i h_{t-i}$$

where R_t is the daily return at time t; z_t is the unconditional variance of daily returns at time t; h_t is the conditional variance of the daily returns at time t; ε_t is the unexpected daily return that cannot be predicted based on all information available up to the preceding period

***, ** and * indicate the statistical significance level at 1, 5 and 10%, respectively; p-values are reported in (·)

CPO – daily crude palm oil spot return; *RPKO* – daily RBD palm kernel oil spot return; *FPOL* – daily RBD palm olein futures return; *FPKO* – daily crude palm kernel oil futures return; *RPO* – daily RBD palm oil spot return; *FCPO* – daily crude palm oil futures return, *RPOL* – daily RBD palm olein spot return; *RPST* – daily RBD palm stearin spot return; RBD – refined, bleached and deodorized

ARCH-LM – Lagrange multiplier test for autoregressive conditional heteroscedasticity; $Q(20)$ and $Q^2(20)$ stand for the Ljung-Box test statistics for autocorrelation of standardised residuals and squared standardised residuals up to 20 lags, respectively; SIC – Schwarz information criterion; for further explanation please refer to section of data and methodology

Source: authors' own estimation based on data provided by the Bursa Malaysia (2018)

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Table 3. Cross-correlation analysis between spot and futures returns

	Causality in mean		Causality in variance	
Cross-correlation analysis between refined palm oil spot and unrefined palm oil futures returns				
k	*FCPO* ⟶ *RPO*	*RPO* ⟶ *FCPO*	*FCPO* ⟶ *RPO*	*RPO* ⟶ *FCPO*
5	1.5052*	–1.0951	–1.4272	–1.4341
10	2.1286**	–1.1580	–1.7659	–1.9944
15	1.2557	–1.2979	–2.2851	–2.4577
20	0.6862	–1.6682	–2.6760	–2.8518
25	0.4049	–1.4836	–3.0278	–3.0766
30	–0.1733	–1.3456	–3.3675	–3.4102
35	–1.0809	–0.5518	–3.5663	–3.0581
40	3.3183***	–0.8783	30.7351***	–3.2764
k	*FCPO* ⟶ *RPST*	*RPST* ⟶ *FCPO*	*FCPO* ⟶ *RPST*	*RPST* ⟶ *FCPO*
5	90.1122***	–0.0520	–0.5023	–0.9637
10	64.1981***	–0.3512	–1.2460	–0.7308
15	52.7453***	–0.6648	–0.8683	–1.2730
20	45.3744***	–0.7047	–0.5364	–1.0175
25	41.0366***	–0.7280	–1.0728	–0.6922
30	37.5834***	–0.8359	–0.8903	–0.7695
35	2.1428**	–1.4917	–1.3487	–0.1808
40	31.8115***	–1.1793	–1.4255	–0.3903
k	*FCPO* ⟶ *RPOL*	*RPOL* ⟶ *FCPO*	*FCPO* ⟶ *RPOL*	*RPOL* ⟶ *FCPO*
5	31.8057***	–0.0686	–0.6804	0.5018
10	22.83***	–0.8151	–0.6594	1.0435
15	18.4008***	–0.7542	–1.1809	0.3327
20	15.5419***	–0.9146	–1.4965	0.2443
25	13.8789***	–1.4258	–1.4460	–0.3207
30	12.9701***	–0.5986	–1.1926	–0.4913
35	–0.7384	–0.3683	–1.6385	–0.5556
40	10.8617***	0.1113	–1.6052	–0.5762
k	*FPKO* ⟶ *RPKO*	*RPKO* ⟶ *FPKO*	*FPKO* ⟶ *RPKO*	*RPKO* ⟶ *FPKO*
5	–0.9233	9.911***	–0.9124	11.9693***
10	–0.8158	17.3263***	–0.9004	10.9628***
15	–0.6553	16.1843***	–1.3025	9.3424***
20	–1.2215	15.3433***	–1.666	10.5042***
25	–1.5328	15.0722***	–2.1248	8.9998***
30	–1.2596	13.7445***	–2.4134	7.7826***
35	–1.7410	10.8820***	–1.7397	2.8000***
40	–1.4622	11.6702***	–1.5899	7.0807***
Cross-correlation analysis between unrefined palm oil spot and refined palm oil futures returns				
k	*CPO* ⟶ *FPOL*	*FPOL* ⟶ *CPO*	*CPO* ⟶ *FPOL*	*FPOL* ⟶ *CPO*
5	0.1118	–0.7409	–1.3118	–1.1187
10	0.295	–0.0324	–1.9376	–1.7350
15	0.555	0.3254	–1.0086	–2.3018
20	1.2566	0.5363	–0.5837	–2.6744

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Continuation Table 3

	Causality in mean		Causality in variance	
Cross-correlation analysis between unrefined palm oil spot and refined palm oil futures returns				
k	*CPO* → *FPOL*	*FPOL* → *CPO*	*CPO* → *FPOL*	*FPOL* → *CPO*
25	0.9806	0.6378	−1.1179	−3.0258
30	0.5897	1.1046	−1.5419	−3.2398
35	0.4736	0.5379	−1.8369	−3.6216
40	−0.0166	0.3711	−2.1487	−3.7666

***, ** and * indicate the statistical significance level at 1, 5 and 10%, respectively; reported test statistics are based on one-tailed tests; test statistics are used to test the null hypothesis of no causality from lag 1 to lag k (k = 5, 10, 15, 20, 25, 30, 35, 40 days); *FCPO* – daily crude palm oil futures return, *RPO* – daily RBD palm oil spot return, *RPST* – daily RBD palm stearin spot return; *RPOL* – daily RBD palm olein spot return, *FPKO* – daily crude palm kernel oil futures return and *RPKO* – daily RBD palm kernel oil spot return; *CPO* – daily crude palm oil spot return; *FPOL* – daily RBD palm olein futures return; RBD – refined, bleached and deodorized

Source: authors' own calculation

AR stands for autoregressive). In Table 2, ARMA (1, 1) – GARCH (1, 1) and ARMA (1, 1) – GARCH (1, 1) models are selected for *FCPO* and *RPOL*, respectively. Since a parsimony model does not sufficiently capture the heteroscedasticity of *RPST*, a high order GARCH model is called for.

The parameters in each selected model specification are estimated with a generalised error distribution (GED) as described by Box and Tiao (1973). We follow Nelson (1991) and Zhong et al. (2004) who consider such an error distribution in modelling asymmetric GARCH effect. Most of the coefficients for ARCH and GARCH terms at higher order are statistically significant. The sum of coefficients for both terms is less than unity, indicating that volatility persistence for all returns is stable.

For diagnostic checking, $Q(20)$ and $Q^2(20)$ represent the Ljung-Box statistics in testing the null hypothesis of no serial correlation up to order 20 for standardised residuals and squared standardised residuals, respectively. ARCH-Lagrange Multiplier (LM) statistics are used to test the null hypothesis of homoscedasticity. As shown in Table 2, both test statistics for $Q^2(20)$ and ARCH-LM are well above the 5% significance level in all cases. This supports that the selected model specifications fit these data adequately.

The results based on Hong's (2001) statistic values from lag 1 to lag k (k = 5, 10, 15, 20, 25, 30, 35 and 40 days) as reported in Table 3. There are four interesting findings. First, there is evidence of causality from the mean of crude palm oil futures returns to RBD palm oil, RBD palm stearin and RBD palm olein spot

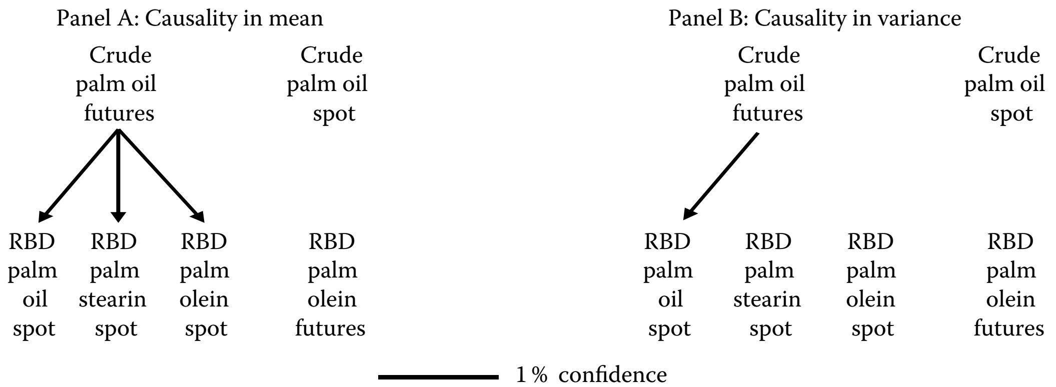

Figure 1. Causality in mean and variance between crude palm oil and refined palm oil returns by test statistics from lag 1 to lag k

k = 5, 10, 15, 20, 25, 30, 35 or 40 days; RBD – refined, bleached and deodorized

Source: author's own sketch

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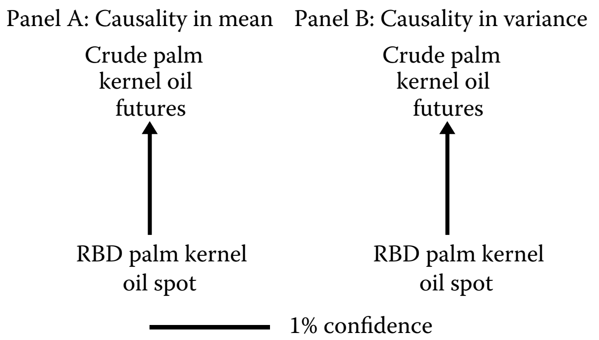

Figure 2. Causality in mean and variance between crude palm kernel oil and refined palm kernel oil returns by test statistics from lag 1 to lag *k*

k = 5, 10, 15, 20, 25, 30, 35 or 40 days; RBD – refined, bleached and deodorized

Source: author's own sketch

returns. Crude palm oil futures returns cause RBD palm stearin and RBD palm olein spot returns in the mean of which lasts for 30 days at the 1% level. Crude palm oil futures returns at the 10, 5 and 1% levels cause RBD palm oil returns in mean at lags of 5, 10 and 40 days, respectively. By contrast, the reverse causality (refined palm oil spot returns to crude palm oil futures returns) is not significant (Table 3 and Panel A of Figure 1).

Second, when *k*-lags are equal to 5, 10, 15, 20, 25, 30, 35 and 40 days, the 1% significance level of causality in mean is found to flow from RBD palm kernel oil spot returns to crude palm kernel oil futures returns (Table 3 and Panel A of Figure 2). The causality in variance for a similar direction is also found at low and high lag orders (Table 3 and Panel B of Figure 2).

Third, we find evidence of causality in variance from the crude palm oil futures market to the RBD palm oil spot market at the lag of 40 days (Table 3 and Panel B of Figure 1). This finding shows volatility spillover from unrefined palm oil futures returns to refined palm oil spot returns happens at a higher order lag.

Surprisingly, there is no information flow between RBD palm stearin spot and crude palm oil futures markets, as well as between RBD palm olein spot and crude palm oil futures markets (Table 3 and Panel B of Figure 1). One possible reason is that most consumers do not have prior experience in the handling of these products. No evidence of information flow is found between crude palm oil spot and RBD palm olein futures markets (Table 3 and Panel B of Figure 1).

CONCLUSION

This study examines the causality between spot and futures returns in the case of unrefined and refined palm oil products. Our results show: first, there is a significant unidirectional causality in mean from crude palm oil futures returns to RBD palm oil, RBD palm stearin and RBD palm olein spot returns. Second, for palm kernel oil-related products, a significant opposite direction of causality in terms of mean and variance is found to flow from RBD palm kernel oil spot returns to crude palm kernel oil futures returns. This implies substantial growth of demand for refined palm kernel oil of which it encourages more trades in the futures market. Third, a significant causality in variance is found to happen from crude palm oil futures returns to RBD palm oil spot returns at a higher order lag. To confront exogenous event such as weak currency, their risk adverse behavior resulted in a longer time span for the volatility of crude palm oil and RBD palm oil spot markets.

Our empirical findings are relevant for refiners in reducing production costs. First, they are suggested to focus on crude palm oil futures returns for predicting future spot returns of refined palm oil products. Second, they are suggested to lock in the purchasing price of unrefined palm oil products. Hence, they can trade crude palm kernel oil futures contracts as input hedge towards their perceived risk.

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