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# THE ROLE OF PALM OIL IN STABILISING THE PRICE OF VEGETABLE OIL MARKET: EMPIRICAL EVIDENCE USING MGARCH APPROACH

TAMAT SARMIDI[1,3]*, ABDUL HAFIZH MOHD AZAM[1], ABU HASSAN SHAARI MD NOR[1] AND KALSOM ZAKARIA[2]

*[1]Center for Sustainable and Inclusive Development Studies, Faculty of Economics and Management, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia. [2]Economics and Industry Development Division, Malaysian Palm Oil Board, Bandar Baru Bangi 43000 Kajang, Selangor, Malaysia. [3]Departemen Ilmu Ekonomi, Fakultas Ekonomi dan Bisnis, Universitas Airlangga, Kampus B Jl. Airlangga No 4-6 Surabaya, 60115 East Java, Indonesia.*

**Corresponding author: tamat@ukm.edu.my*
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**Abstract:** This paper investigates the dynamic relationship among four major vegetable oils for both the first and second moment using the Multivariate GARCH model under Baba, Engle, Kraft and Kroner (BEKK). The result from the first moment, which is return spillover, shows palm oil emerges as a vital source of the spillover, while rapeseed oil shows non-dominance to any edible oils. Meanwhile, the second-moment analysis shows volatility spillover from palm oil and soybean oil to other edible products, but no one dominates in shock transmission. Evidence of the bidirectional causality in both first and second moments for most edible oils show less opportunity for diversification strategy in the vegetable oil market. On the other hand, the result suggests stabilizing palm oil price volatility is necessary to reduce vegetable oil price uncertainty. This finding might help policymakers propose appropriate risk mitigation strategies in the vegetable oil market to ensure price stability.

Keywords: Volatility spillover, shock transmission, vegetable oils, BEKK, multivariate student's-t distribution.

## Introduction

The price of vegetable oils has been relatively stable until the food crisis in 2007-2008. The price of major world vegetable oils like soybean, sunflower and palm has doubled from \$699, \$730, and \$583 per metric tonnes in December 2006 to \$1511, \$1692, and \$1128 per metric tonnes, respectively, in July 2008 (UNCTAD, 2018). As shown in Figure 1, prices of vegetable oils and West Texas Intermediate Crude Oil (WTI) are moving in tandem up to mid-2008 and move apart only after the food crisis. The co-movements between vegetable oils and crude oil prices could be due to the direct cost of transportation, machinery, and fertiliser to the agricultural sector (ODI, 2008). This new evidence has invited an exciting debate in the area of price discoveries among the commodity markets.

In the vegetable oil market for the year 2017/2018, palm oil constitutes about 35% of total world production (198.68 Million Metric Tonnes), followed by soybean oil 28%, rapeseed oil 14%, sunflower oil 9% and others 13% (USDA, 2018). Palm oil constitutes also makes up the most considerable portion of global imports at 63% or 75.31 Million Metric Tonnes, followed by soybean oil 14%, sunflower oil 11%, rapeseed oil 6%, and others 11% (USDA, 2018). Palm oil also conquered exports at 62% or 81.25 million metric tons, followed by soybean 13%, sunflower oil 12%, and rapeseed oil 6% (USDA, 2018). The fact that palm oil comprises a large portion of both production and trade in the vegetable oils market, gives rise to the question, does palm oil influence the price of other vegetable oils given that these vegetable oils are highly substitutable (In & Inder, 1997), and palm oil prices are relatively lower than other edible oils (Figure 1). Therefore, the vegetable oil price's long-run co-movement could be due to a higher degree of substitutability among them, making the price not likely to deviate from each other (In & Inder, 1997).

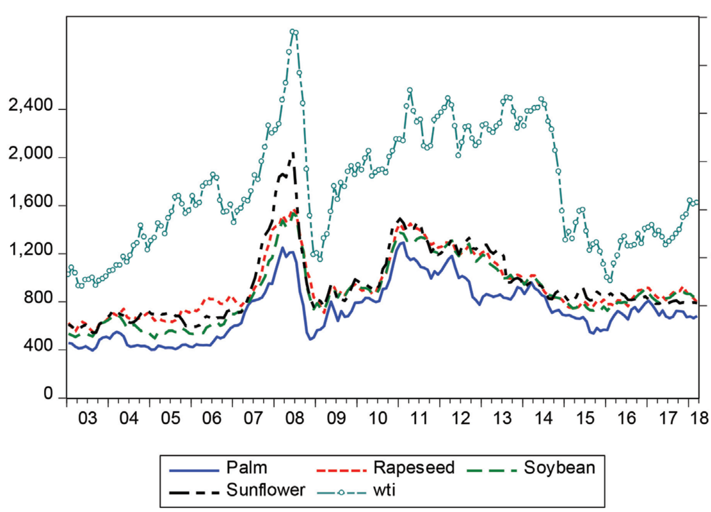


Figure 1: Price of vegetable oils and West Texas Intermediates Crude Oil (WTI)
Notes: Left scale refers to the price of vegetable oils, while the right scale for crude oil

It is well known that variance of returns is often used as a proxy for risk (Lim & Sek, 2013; Sewell, 2011). It can influence investors' level of return gain because, according to portfolio theory, high risk is accompanied by high expected return (Surianshah *et al.,* 2014). In the vegetable oil market, the volatility of edible oil returns can affect farmers' income and stability of price (Bergmann *et al.,* 2016). The volatility of edible oil can spill to another oil due to the high-level price co-movement among them (Figure 1). Therefore, it is natural to ask whether there is any transmission of risk among vegetable oils. This question can help determine the causality of risk as well as establishing which edible oil are more exposed to the risk from their substitutes. An important conclusion, such as diversification strategy and hedging, might be drawn from the empirical analysis of the vegetable oil market's risk. For example, a strategy to put all edible oil assets in a portfolio will not optimize the expected return due to high co-movement among all edible oil prices' variance if not in mean or level form. It also justifies the need for a second-moment analysis of risk spillover among edible oils. In many cases, the transmission between level forms may not be significant but is pertinent in the variance form (Engle, 2001; Brooks & Persand, 2003).

Thus, this paper aims to investigate the relationship among four major vegetable oil through both first- (mean) and second-moment (variance) by using Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) model under the formulation of Baba, Engle, Kraft and Kroner (BEKK). The use of MGARCH was initially proposed by Bollerslev *et al.* (1988) under the formulation of VECH before Engle and Kroner (1995) popularized the BEKK model. Given the MGARCH model features, which can simultaneously model the volatility across asset and market, the model is more relevant than the univariate GARCH (Bauwens *et al.,* 2006).

The paper is organised as follows:

The second section is a brief discussion of the vegetable oil market literature that focuses on the second-moment framework. The third and the fourth sections describe the research methodology and the empirical results, respectively. The conclusion and policy implications are in the last section.

## Literature Review

The bulk of the study focuses on examining the volatility spillover in the stock market to determine their interdependence and contagions regardless of whether it comes from developed, emerging or developing countries. However, the vegetable oil market literature rarely discusses the second-moment relationship, giving valuable information to the existing first-moment analysis. Current studies on the vegetable oil market are mainly concerned with the long-run relationship between vegetable oil price and their degree of substitutability to assess the price stability of the world vegetable oil market.

One of the empirical works on determining the world vegetable oil price's co-movements has been discussed by In and Inder (1997). They investigated the co-movements of eight vegetable oil prices using Johansen and Juselius (1990) cointegration approach. In and Inder's (1997) empirical result show four cointegration vectors, and the vegetable oils tend to be grouped according to their end-uses. On the other hand, using the same approach, Owen *et al.* (1997) does not find strong evidence to conclude the long-run relationship between vegetable and tropical oils. However, they find that sunflower and soybean prices interact more significantly with coconut, palm and palm kernel oil prices. Meanwhile, using the Engle-Granger two-step procedure, Alias and Othman (1998) found sufficient evidence to conclude that palm and soybean oil prices move together in the long run, and there exist bidirectional Granger causality among them.

Several studies concentrate on the interaction between crude oil price with vegetable oil price due to the food crisis in 2008. Hameed and Arshad (2009) investigate the long-term relationship between the price of crude oil and selected vegetable oils using a bivariate Engle-Granger two-step cointegration methodology. Their study finds long-run co-movements between petroleum price and each of the four vegetable oils (palm, soybean, rapeseed and sunflower oil). However, Peri and Baldi (2010) did not find cointegration between soybean and sunflower seed oil with diesel but did find cointegration in rapeseed oil.

Nevertheless, the outcome could be different due to different techniques, time span, frequency of data and proxy. Kiatmanaroch and Sriboonchitta (2014) suggest that ASEAN countries should not rely on imported soybeans since the crude oil price influences the price. Instead, ASEAN countries must cooperate in providing a practical plan for food price security. On the other side, evidence of crude oil price influencing other commodities has been documented by Nazlioglu *et al.* (2013). They found evidence of volatility spillover from oil to the agricultural market except sugar during the post-food crisis period.

On the second-moment analysis, Brümmer *et al.* (2016) studied the potential exogenous volatility driver and spillovers effects of major oilseeds and vegetable oils prices. The study, employing standardised GARCH framework and VAR model, finds that palm oil and soybean oil price volatility is the most substantial "driver" on other major oilseeds and vegetable oil prices. In a different study, Yu *et al.* (2006) claim that soybean oil significantly impacts uncertainty in other edible oil by about 31.82% – 75.01%. However, they further argue that the palm oil market could initiate new information to other edible oils. Lahiani *et al.* (2013) investigate the volatility spillover among sugar, cotton, wheat, and corn in the agriculture commodity market. The results showed the dominance of corn in transmitting the volatility spillover to other markets while no direct transmission is found from wheat to the remaining market. Hamadi *et al.* (2017) investigated the interdependence of agricultural commodities. They found that volatility spillover is pronounced from soybean and soybean oil to wheat and corn market rather than the inverse. On top of that, the growing interest in biofuel has intensified research on the commodity. Dutta *et al.* (2018) examined the impact of uncertainty in the corn market on US ethanol prices using the GARCH-jump model. They found that the implied volatility index of corn plays a vital role in influencing the US ethanol price. Meanwhile, in a more recent study by Dutta *et al.* (2021), the crude oil volatility index (OVX) was found to have a significant negative impact on palm oil price, i.e., increasing OVX leads to a decrease in price.

On the futures and spot market of the palm oil research, Feng *et al.* (2003) find a bidirectional volatility spillover between futures and spot markets. The study indicates that the market leader is not identifiable in this context. In addition to various markets relationship, Sy *et al.* (2015) examine volatility spillover from the futures market of soybean oil to the futures and spot market of palm oil. The empirical result using trivariate volatility shows significant volatility from the soybean futures market to spill over to both the palm oil market. Nonlinear modelling on vegetable oil prices were conducted by Ismail (2011) using Markov Switching-VAR. Even though the result showed no cointegration between variables, interestingly, he found that all vegetable oils except olive oil were more volatile during the periods when prices were increasing. The financialisation of the oil market has been studied by Saiti *et al.* (2014). Using palm oil price, exchange rate, and the stock market in Malaysia, the authors revealed that the stock market had led palm oil in the long run but found no evidence of a lead-lag relationship between palm oil and exchange rate.

The use of wavelet methodology has gained attention from researchers in the field of economics and finance. Wavelet methodology allows the analysis across the time-frequency domain to offer more insight than ordinary time series analysis. Mensi *et al*. (2017) investigated the dependence structure between implied volatility indexes of oil, wheat, and corn using a combination of wavelet and copula models. The empirical results showed the existence of time-varying asymmetric tail dependence among the three commodities at different time horizons. In addition, a recent study by Azam *et al.* (2020) used wavelet multiple cross-correlations to analyze the lead-lag relationship among the prices of the world major vegetables oils (rapeseed, soybean, palm and sunflower oil). Their study showed that soybean prices led all the vegetable oil prices on all horizons.

**Methodology**

The study employs monthly price data of soybean, sunflower, palm and rapeseed oil to represent the world vegetable oil market. The dataset ranges from January 2003 until March 2018, derived from the open-source website of the United Nations Conference on Trade and Development (UNCTAD)[1] and the International Monetary Fund (IMF)[2]. Prices of sunflower and palm oil are the CIF and FOB prices ina North-Western European port respectively, while rapeseed and soybean oil are the FOB prices in Rotterdam and FOB ex-mill prices in the Netherlands. All prices are in USD per Metric Tonnes.

Most of the current studies in volatility spillover effect employ techniques such as causality in variance, vector autoregressive (VAR) and impulse response function (IRF), Cheung and Ng (1996), Hong (2001) and Hafner and Herwartz (2006), among others. Unlike the existing studies, this study adopts the Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) model by Baba, Engle, Kraft and Kroner (BEKK). The BEKK approach modeled the volatility spillover and shock transmission simultaneously without aggregating both components like the aforementioned model. Preceding the test of causality in variance, Cheung and Ng (1996), Hong (2001) and Hafner and Herwartz (2006) used the residual from univariate GARCH while VAR and IRF utilized the conditional variance from a given model. However, that approach (2-step estimation) might be not efficient (McMillan & Speight, 2010) compared to a one-step estimation by BEKK. In the case of a time-varying correlation coefficient, Engle has shown that two-step estimation yields consistent estimates. Still, it is not as efficient as a one-step estimate, like BEKK (Enders, 2010). Given that edible oil prices move together (as shown in Figure 1), there might be a potential leader among the oils that drives the price. In addition,

1 http://unctadstat.unctad.org/EN/Index.html
2 http://www.imf.org/external/

the uncertainty or risk from oil leaders also tends to spill over to the rest of the vegetable oils market. Thus, using the MGARCH model is sufficient to determine first and second-moment feedback among vegetable oils that are interrelated.

On the other hand, the mean equation of the given GARCH model should be specified correctly to avoid any misspecification that could carry into the variance equation (Enders, 2010). Therefore, to investigate the volatility spillover and shock transmission among vegetable oils, one should also consider multivariate mean models for vegetable oil since they are interrelated. Furthermore, several papers discussing o agricultural commodities and vegetable oils have used non-Gaussian distribution to model the fat tail phenomenon (see Hamadi *et al.,* 2017; Brümmer *et al.,* 2015; Kiatmanaroch & Sriboonchitta, 2014). As for this, we proposed Vector Autoregressive-Baba, Engle, Kraft and Kroner with Student's-t distribution (VAR-BEKK-t) to analyze the interdependence of the vegetable oil market.

Variables are assumed to behave as a stationary process before entering the VAR model (Enders, 2010). Hence, continuously compounded return (return) of vegetable oils is utilized in this study, and it is computed as the log difference of monthly price or $r_t = log\ log\ (P_t) - log\ log\ (P_{t-1})$ where and are monthly prices at current month and previous month, respectively. The VAR(1)-BEKK(1,1) takes the following form:

$$R_t = \pi_0 + \pi_1 R_{t-1} + \varepsilon_t \quad (1)$$

Equation (1) is the VAR model for the mean equation where $R_t$ is ($n$ x 1) vector containing $n$ variables in VAR, is ($n$ x 1) vector of a constant term, is ($n$ x $n$) matrices of coefficient and is ($n$ x 1) vector of the error term.

$$H_t = C'C + A_i'\varepsilon_{t-1}\varepsilon_{t-1}'A_i + B_i'H_{t-1}B_i \quad (2)$$

Equation (2) is the BEKK model introduced by Engle and Kroner (1995) for the variance equation. A and B are the $n$ $x$ $n$ matrices and to ensure the intercept of the off-diagonal elements of is identical, C must be in $n$ $x$ $n$ matrix (Enders, 2010). Furthermore, A and B's off-diagonal elements measure the shock transmission and volatility spillover while diagonal elements measured their own effects. It is important to note that the BEKK model is not globally identified. Thus, changing the entire A or B matrix sign will give exactly the same fit (Doan, 2014). Meanwhile, as documented by Tsay (2006), the parameter of BEKK is hard to interpret.

## Empirical Result

Table 1 shows descriptive statistics for the return of soybean oil (RSOY), sunflower oil (RSUN), palm oil (RPALM) and rapeseed oil (RSEED). The mean value for all vegetable oil returns is positive, with soybean oil having the highest average positive return (0.24%), palm oil (0.22%), and sunflower and rapeseed oil with 0.14%. Among the four vegetable oils, palm oil had created a 1-month huge profit (16%) and 1-month huge loss (35%) from February 2003 until March 2018. The standard deviation is associated with uncertainty, and it is interesting to note that rapeseed oil shows the lowest standard deviation compared to other edible oils. However, according to the coefficient variation (CV), soybean oil shows a better risk-return trade-off.

Moreover, all vegetable oil returns show a negatively skewed distribution, indicating that the fall in returns is more likely than an increase. The kurtosis value for all series is greater than 3 to show the leptokurtic distribution of the fat tail phenomenon. The Jarque-Bera test for normality rejects the null hypothesis of normal distribution, thus leading to the use of Student's-t distribution to capture the fat tail behavior. The significant return and return squared dependency for all series indicate both mean and variance equations are simultaneously affecting each other. The mean equation can be modeled through the VAR model while the variance equation for BEKK is utilized.

Table 1: Descriptive statistics

| | RSOY | RSUN | RPALM | RSEED |
|---|---|---|---|---|
| Mean | 0.0024 | 0.0014 | 0.0022 | 0.0014 |
| Median | 0.0023 | 0.0034 | 0.0043 | 0.0000 |
| Maximum | 0.1173 | 0.1513 | 0.1603 | 0.1451 |
| Minimum | -0.2785 | -0.2490 | -0.3469 | -0.1701 |
| Std. Dev. | 0.0493 | 0.0590 | 0.0658 | 0.0487 |
| CV | 20.2284 | 42.0378 | 30.1807 | 35.8191 |
| Skewness | -0.8944 | -0.7516 | -0.9896 | -0.0790 |
| Kurtosis | 8.1030 | 6.1681 | 7.4331 | 4.1304 |
| Jarque-Bera | 221.7413 (0.0000) | 93.2486 (0.0000) | 178.7357 (0.0000) | 9.8796 (0.0072) |
| Q [4] | 41.244 (0.0000) | 50.799 (0.0000) | 29.224 (0.0000) | 36.363 (0.0000) |
| Q [8] | 44.861 (0.0000) | 53.318 (0.0000) | 44.155 (0.0000) | 39.826 (0.0000) |
| $Q^2$ [4] | 26.510 (0.0000) | 56.654 (0.0000) | 24.757 (0.0000) | 68.049 (0.0000) |
| $Q^2$ [8] | 31.666 (0.0000) | 62.665 (0.0000) | 34.057 (0.0000) | 83.919 (0.0000) |

Notes: The number in bracket is the number of lags while the number in parentheses is the p-value. Q stand for Ljung-Box Q statistics for return dependency while Q2 stand for Ljung-Box Q squared statistics for return squared dependency

The appropriateness of error distribution used in modeling the vegetable oil return can be referred to in Figure 2 below. The Figure shows the kernel density plot of vegetable oil returns using both Gaussian and Student's-t distribution. In order to determine which distribution is chosen, the one that can better fit the kernel of vegetable oil returns will be selected. The graphical plot below shows that the Student's-t distribution is much better in fitting the kernel of RSUN and RPALM while slightly better for RSOY compared to the Gaussian distribution. However, for the kernel of RSEED, each distribution seems cannot fit the kernel especially the kurtosis part. In this case, the t-distribution is likely to overestimate the kurtosis. This is true due to the small excess of kurtosis and skewness in RSEED.

In order to deal with the VAR-BEKK approach, one must satisfy the assumption on the stationary of the series. Table 2 shows the unit root test result on the price and return of vegetable oil. Two types of mainstream unit root tests, namely Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), are used to determine the series' stationarity. The null hypothesis of both tests indicates the series have a unit root, which means the series are non-stationary. The result from Table 2 shows the non-rejection (rejection) of the null hypothesis for the price (return) series of vegetable oils, indicating the series are non-stationary (stationary). Thus, it can be concluded that the return of vegetable oil is stationary or integrated of order 0 or I (0).

Table 3 shows the estimation using the VAR-BEKK-t approach to estimate volatility spillover and shock transmission among vegetable oil returns. The empirical result from the first panel (mean equation) shows soybean oil return is strongly affected by its previous lag and lags from the sunflower and palm oil return. There is strong evidence (1% significant level) of return spillover from palm oil to sunflower oil, but weak evidence (10% significant level)

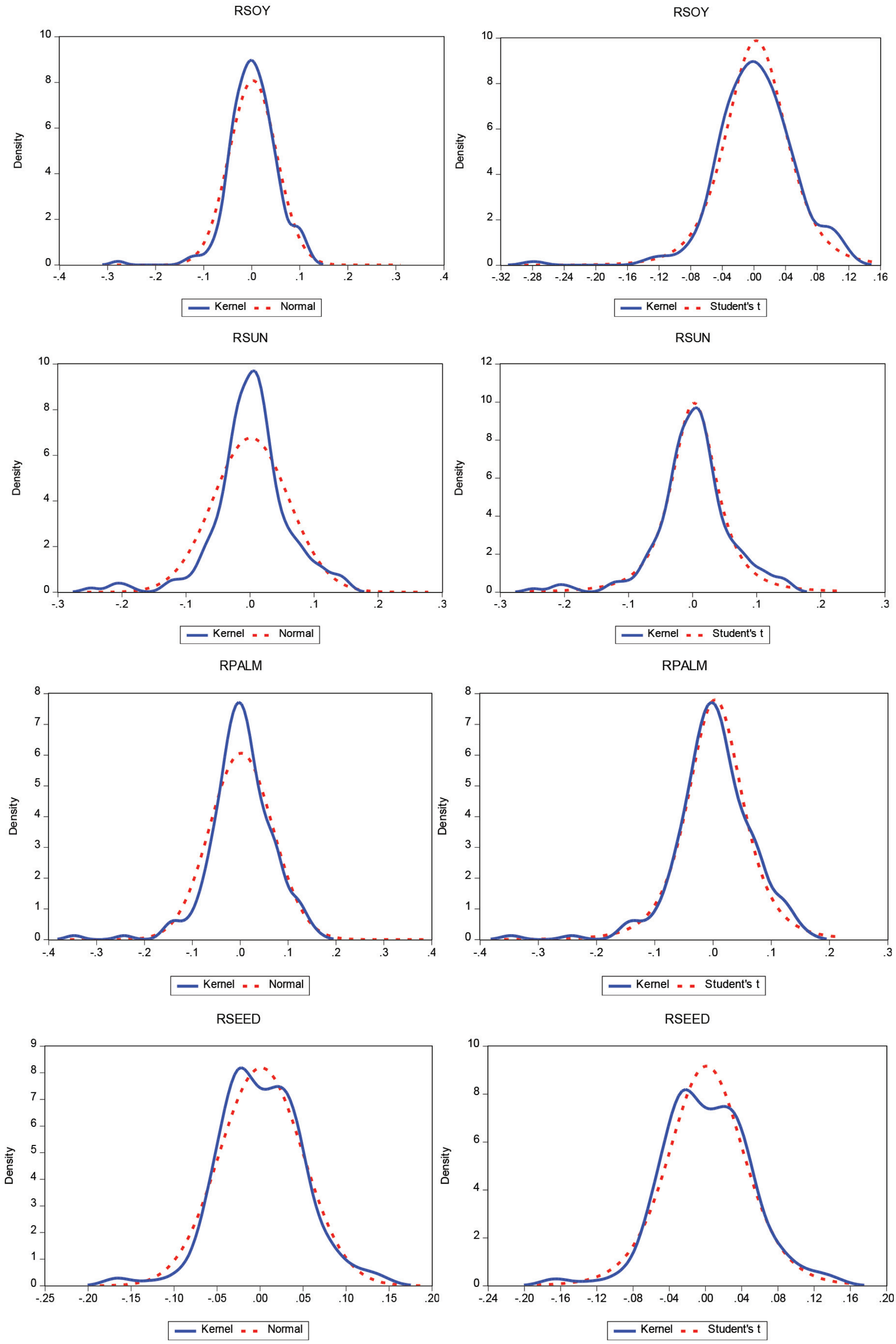


Figure 2: Kernel density plots for the return of vegetable oils

Table 2: Unit root test

| Series<br>ADF | | Level<br>PP | | Specification |
|---|---|---|---|---|
| Soybean Oil | Price | -2.1386 | -2.0477 | T + I |
| | Return | -8.9595*** | -9.1536*** | I |
| Sunflower Oil | Price | -2.7351 | -2.3978 | T + I |
| | Return | -8.072*** | -8.0461*** | I |
| Palm Oil | Price | -2.3991 | -2.1375 | T + I |
| | Return | -9.1144*** | -9.1115*** | I |
| Rapeseed Oil | Price | -2.1966 | -2.1297 | T + I |
| | Return | -8.953*** | -9.0626*** | I |

*** indicates significant at 1%. I = Intercept and T = Trend

is found inversely. Furthermore, soybean oil return shows a spillover effect on palm oil and there exist unidirectional return spillover from soybean, sunflower and palm oil to rapeseed oil. In contrast, rapeseed oil offers non-dominance in return spillover to other edible oils. A similar conclusion arises from Yu *et al.* (2006), whereby rapeseed oil is an information receiver but not an information provider to other edible oils. Meanwhile, palm oil emerges as the only substantial source of return spillover to other vegetable oils. The result is consistent with its world edible oils production share dominance, where palm oil controls almost 35 per cent of the world production compared to rapeseed oil, which only has a 6 per cent production share. In terms of the application of vegetable oils, palm oil has broader usage compared to rapeseed and soybean, especially in processed foods and fried snacks (Cassiday, 2017).

The second panel of Table 3 shows the coefficient of the variance equation estimation. There is a mixed result from the analysis, and it might be due to strong potential substitution among the vegetable oil prices as concluded by Brümmer *et al.* (2016). The result indicates that the conditional variance of soybean oil is not affected by its past shock. At the same time, there is a unidirectional shock transmission from rapeseed oil to soybean and a bidirectional shock transmission between soybean oil and sunflower oil. It is also evident that the sunflower oil conditional variance is also affected by its own shock and shock from palm oil. In addition, the conditional variance of rapeseed oil is being affected by its own past shock and shock from palm and sunflower oil. Furthermore, it is interesting to highlight the non-existence of shock transmission to conditional variance of palm oil, indicating that palm oil is not sensitive to the news in the vegetable oil market. The non-sensitivity of palm oil conditional variance to news (shock) on the other vegetable oil might be due to the feature of the palm oil itself. For example, palm oil is a tropical plant, and the growth and yield of oil palm trees depend mainly on the climatic characteristics of the environment (Kamil & Omar, 2017). By assuming countries that face major climate issues, such as floods or extreme temperature changes, could cause a decline in production, this will not increase the risk of palm oil due to different land types and zones.

Our empirical study also shows that while there is an absence of spillover on the first moment, there is evidence of spillover on the second moment from rapeseed oil returns to other vegetable oils. It is worth highlighting that the first and the second moments have different characteristics. Spillover in the first moment primarily focuses on the return of the vegetable oil price. Hence, given that the price of rapeseed oil is higher than soybean and palm oil (Figure 1) and its portion on global trade is very small, intuitively, it does not have spillover to the rest of vegetable oil returns. However, the

Table 3: Volatility spillover and shock transmission among vegetable oil returns using VAR-BEKK-t

| Commodity | RSOY | RSUN | RPALM | RSEED |
|---|---|---|---|---|
| ***Mean Equation*** | | | | |
| Constant | 0.0017 | 0.0047* | 0.0007 | 0.0009 |
| $RSOY_{t-1}$ | 0.3156*** | 0.0801 | 0.4336*** | 0.2150*** |
| $RSUN_{t-1}$ | 0.2336*** | 0.5303*** | 0.1355* | 0.2735*** |
| $RPALM_{t-1}$ | -0.127*** | -0.1505*** | -0.0082 | -0.1524*** |
| $RSEED_{t-1}$ | -0.0022 | 0.0437 | -0.1515 | 0.0960 |
| ***Variance Equation*** | | | | |
| C(1,1) | -0.0001 | | | |
| C(2,j) | -0.0034 | 0.0165*** | | |
| C(3,j) | 0.0026 | -0.0133*** | 6.60E-07 | |
| C(4,j) | 0.0013 | -0.0071*** | 2.46E-06 | 6E-09 |
| $\varepsilon^2_{t-1,rsoy}$ | 0.0433 | 0.9183*** | 0.0543 | -0.0959 |
| $\varepsilon^2_{t-1,rsun}$ | -0.368*** | -0.4879*** | -0.0260 | -0.2341*** |
| $\varepsilon^2_{t-1,rpalm}$ | -0.0466 | -0.4409*** | -0.0207 | -0.2979*** |
| $\varepsilon^2_{t-1,rseed}$ | 0.3285*** | 0.1277 | 0.0948 | 0.7211*** |
| $\sigma^2_{t-1,rsoy}$ | 0.2032** | -0.7721*** | -1.1738*** | -0.2933*** |
| $\sigma^2_{t-1,rsun}$ | 0.1467 | 0.3889*** | 0.4781*** | -0.0343 |
| $\sigma^2_{t-1,rpalm}$ | 0.5929*** | 0.5813*** | 1.1350*** | 0.4200*** |
| $\sigma^2_{t-1,rseed}$ | -0.2275* | 0.3852*** | -0.1394 | 0.6851*** |
| Shape | 8.2260*** | Log Likelihood | 1442.5935 | |
| ***Diagnostic*** | | | | |
| MVLB-Q [4] | 68.4570 | | MVLB-QSQ[4] | 44.7483 |
| | (0.3286) | | | (0.9678) |
| MVLB-Q [8] | 134.8626 | | MVLB-QSQ [8] | 107.7334 |
| | (0.3217) | | | (0.9029) |
| MVLB-Q [12] | 212.2896 | | MVLB-QSQ[12] | 186.0976 |
| | (0.1504) | | | (0.6065) |

***, **, * indicates significant at 1%, 5% and 10%. Number in bracket is the number of lags while the number in parentheses is the p-value. MVLB-Q stand for multivariate Ljung-Box-Q test for autocorrelation and MVLB-QSQ stand for multivariate Ljung-Box-Q squared test for heteroscedasticity

second moment focuses more on the conditional variance of the vegetable oil market, which is related to risk. Usually, the risk is more prevalent during a certain period, such as the food crisis in 2008. However, as the empirical results tend to show average response, it could be the case that the relationship still holds. Therefore, there is spillover from rapeseed oil to other edible oils in the second moment. In addition, the volatility spillover shows the superiority of the second-moment estimation techniques over the first moment (Engle, 2001). In other words, the mean analysis (first moment) could not discover the conditional variance (second moment) relationship between the vegetable oil markets, which is crucial.

The result also shows strong evidence of volatility spillover from palm oil to soybean oil, but weak evidence is found from rapeseed oil. Furthermore, volatility spillover is found from all edible oils to sunflower oil, highlighting those types of vegetable oil are much sensitive to any risk in the vegetable oil market. Besides, the volatility of soybean and sunflower oil are found to spills over to palm oil volatility. At the same time, it is evident that the volatility of soybean and palm oil are found to spills over to the rapeseed oil volatility. While no one dominates in shock transmission, soybean and palm oil show dominance in volatility spillover to other edible oil. This finding is somehow in line with the result reported by Brümmer *et al.* (2016), where palm oil and soybean oil price volatility is the most substantial "driver" on other major oilseeds and vegetable oil prices. Given palm and soybean oils' dominance in the market, any risk associated with these two edible oils might warrant the buyer's attention from rapeseed and sunflower oil.

Besides that, we found some negative parameter for the conditional variance. However, according to Doan (2014), BEKK model is not globally identified. Hence, changing the sign eventually give the same fit. Moreover, the BEKK model ensures the conditional variance are positive by forcing all the parameter to enter the model via quadratic form (Enders, 2010). Thus, there is no issue with the negative parameter, given there is no restriction on the sign of the parameters. Moreover, the shape parameter gives the value of the degree of freedom of the multivariate student's-t distribution. The shape parameter's significance indicates the appropriateness of multivariate Student's-t distribution in this analysis, which considers the fat tail behavior in the vegetable oil market. The last panel in the VAR-BEKK-t results confirm that the Multivariate GARCH estimates are free from autocorrelation and heteroscedasticity problems.

## Conclusion

This paper critically analyzes the dynamic risk behavior of the vegetable oils market. The analysis involves the first- and second-moment relationship among palm oil and other major vegetable oil prices using the Multivariate GARCH model for monthly data from January 2003 to March 2018. Empirical findings using the VAR-BEKK-t approach can be classified into three categories: first, return spillover; second, shock transmission; and third, volatility spillover. The empirical findings show that palm oil strongly influences other vegetable oils for the return spillover; no vegetable oil dominates the shock transmission, and soybean and palm oil show strong dominance in volatility spillover. The MGARCH model is deemed adequate since white noise properties hold, and multivariate Student's-t distribution appears to be well suited for the analysis.

Overall, it can be concluded that palm oil shows a strong influence in leading the vegetable oil price both in the first (mean) and second (variance) moments. Thus, the palm oil price movement could be predicted to trigger a movement in the price of other vegetable oils. In order to reduce the uncertainty in the vegetable oil market, stabilising the price of palm oil is a priority. Thus, this study supports the argument of one price that can regulate others' prices in the undistorted world (Fackler & Goodwin, 2001).

On the other hand, the impact of volatility spillover from soybean to other edible oil should not be underestimated. It is well known that Malaysia and Indonesia, which in the ASEAN region, are palm oil's top producers. Therefore, our result supports Kiatmanaroch and Sriboonchitta (2014) argument that ASEAN countries should provide an effective plan for food price security and stop relying on imported vegetable oil, especially soybean.

From an investment perspective, evidence of bidirectional causality in the mean and variance equation for most edible oils show less opportunity for diversification strategy. However, investors could explore whether the vegetable oil market can serve as an instrument for hedging for different markets, such as precious metals. This finding on the stability of the vegetable oil price is essential for policymakers to propose appropriate risk management to ensure the stability of edible oil products for consumers. Thus, future research can examine the relationship between vegetable oil with the rest of the commodity and financial market.

In summary, the study supports the argument that market regulation could significantly affect the other oil prices in an undistorted world (Fackler & Goodwin, 2001). This paper gives insight to policymakers in formulating policies regarding the stability of the vegetable oil price and investment perspective.

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