Crude oil volatility and the biodiesel feedstock market in Malaysia during the 2014 oil price decline and the COVID-19 outbreak

Author(s): Dutta, Anupam; Bouri, Elie; Saeed, Tareq; Vo, Xuan Vinh

Title: Crude oil volatility and the biodiesel feedstock market in Malaysia during the 2014 oil price decline and the COVID-19 outbreak

Year: 2021

Version: Accepted manuscript

Please cite the original version:

Dutta, A., Bouri, E., Saeed, T. & Vo, X. V. (2021). Crude oil volatility and the biodiesel feedstock market in Malaysia during the 2014 oil price decline and the COVID-19 outbreak. *Fuel*. https://doi.org/10.1016/j.fuel.2021.120221

Fuel

Crude Oil Volatility and the Biodiesel Feedstock Market in Malaysia during the 2014 oil price decline and the COVID-19 outbreak

--Manuscript Draft--

Manuscript Number:	JFUE-D-20-05003R2
Article Type:	Research Paper
Keywords:	Malaysian palm oil prices; Biodiesel; Oil volatility index; Time-varying jumps; Risk transmission; COVID-19 outbreak
Corresponding Author:	Anupam Dutta, Ph.D. Vaasa University Vaasa, FINLAND
First Author:	Anupam Dutta, Ph.D.
Order of Authors:	Anupam Dutta, Ph.D.
	Elie Bouri
	Tareq Saeed
	Xuan Vinh Vo
Abstract:	Although the global crude oil market plays a significant role in pricing edible oils, the association between energy price uncertainty and the Malaysian palm oil industry remains understudied. Given that palm oil is widely used as a cheap feedstock for biodiesel, it is important to investigate whether risk transmits from the oil market to the Malaysian palm oil industry. Employing GARCH-jump models, this study extends the scant literature. The results reveal that the crude oil volatility index (OVX) significantly influences palm oil prices suggesting that an upturn in oil market volatility negatively impacts palm oil prices. Subsample analyses show that the negative impact of the OVX intensifies during the during the 2014 oil price decline and the COVID-19 outbreak. The effect of OVX is asymmetric, implying that changes (upward and downward shifts) in oil price variance exert a heterogeneous impact on the price levels of this edible oil. It is also observed that palm oil prices experience time-dependent jumps. We further document that volatility significantly transfers from the crude oil to the palm oil market during the periods of high uncertainty. Hence, investors and policymakers could use the information content of OVX for forecasting future trends of palm oil prices.

Crude oil volatility and the biodiesel feedstock market in Malaysia during the 2014 oil price decline and the COVID-19 outbreak

Abstract

Although the global crude oil market plays a significant role in pricing edible oils, the association between energy price uncertainty and the Malaysian palm oil industry remains understudied. Given that palm oil is widely used as a cheap feedstock for biodiesel, it is important to investigate whether risk transmits from the oil market to the Malaysian palm oil industry. Employing GARCH-jump models, this study extends the scant literature. The results reveal that the crude oil volatility index (OVX) significantly influences palm oil prices suggesting that an upturn in oil market volatility negatively impacts palm oil prices. Subsample analyses show that the negative impact of OVX intensified during the 2014 oil price decline and the COVID-19 outbreak. The effect of OVX is asymmetric, implying that changes (upward and downward shifts) in oil price variance exert a heterogeneous impact on the price levels of this edible oil. It is also observed that palm oil prices experience time-dependent jumps. We show that volatility significantly transfers from the crude oil to the palm oil market during periods of high uncertainty. Hence, investors and policymakers could use the information content of OVX for forecasting future trends in palm oil prices.

Keywords: Malaysian palm oil prices; Biodiesel; Oil volatility index; Time-varying jumps; Risk transmission; COVID-19 outbreak

1. Introduction

Malaysia is currently one of the leading producers of palm oil in the world. Over the last few decades, the production of crude palm oil (CPO) has increased significantly in Malaysia (Abdul-Mannan et al., 2014; Johari et al., 2015). The amount of CPO produced increased from 2.6 million tonnes in 1960 to over 19.52 million tonnes in 2018 (Malaysian Palm Oil Board (MPOB), 2018). MPOB (2018) reports that the country accounts for 28% of global palm oil production and 33% of world exports[1].

Palm oil, which is the most produced vegetable oil in the world (74 million tonnes in 2018), is widely used as a cheap feedstock for biodiesel. Although biodiesel has similar characteristics to petroleum-based diesel, it is biodegradable, non-explosive, and non-toxic, which significantly reduces toxic emissions from burning (Johari et al., 2015). Misra and Murthy (2011) state that biodiesel contains a low level of sulphur, and add that this type of fuel is completely compatible with conventional diesel and alternative fuels. Biodiesel is thus less harmful to the environment and to human health (Mosarof et al., 2015). Given the global importance of biodiesel as an environmentally friendly fuel, the use of edible oils for biodiesel production has increased significantly over the last decade. As a consequence, the amount of palm oil used for biodiesel production increased from 3.2 to 10.2 million tonnes during the same time.

It is noteworthy that although other edible oils including rapeseed oil, sunflower oil, and soybean oil are used as biodiesel feedstock (Gui et al., 2008; Borugadda and Goud, 2012), the production of CPO is much higher than other oil crops with lower costs (Mosarof et al., 2015). According to

[1] Malaysia currently uses 5.2 million hectares of its land area to produce more than 4 million tonnes of palm kernel oil.

Ashraful et al. (2015): '*The cost of soybean oil is almost 20% higher than palm oil, and rapeseed oil production costs are considerably higher than those of other vegetable oils*'. Lim and Teong (2010) conclude the same. Approximately 75% of global palm oil is used as cooking oil in food manufacturing plants. For these reasons, the use of palm oil has increased all over the world in the last decade.

Malaysia, as a chief exporter of palm oil, has turned out to be a key player in worldwide biofuel production. According to recent statistics published by the Malaysian Palm Oil Board, Malaysia earned RM67.5 billion ($16.16 billion) in revenue from exporting palm oil in 2018 (MPOB, 2018).[2] As Malaysia emerges as a major dealer of this edible oil, the palm oil sector is now considered its key export industry. Hence, palm oil, as a prominent source of biodiesel, is a significant contributor to its national economy. Because the palm oil industry plays such a crucial role in the Malaysian national economy, fluctuations in palm oil prices could bring uncertainty to the country's overall economic growth and development. Thus, it is crucial to recognize the principal factors influencing the vegetable oil sector in Malaysia.

One such factor is crude oil. Since palm oil is an agricultural commodity, its prices might be highly sensitive to variations in crude oil prices. Previous studies claim that palm oil prices are driven by international crude oil prices. Kiatmanaroch and Sriboonchitta (2014) find a positive link between the two markets with exchange rates being a vital factor impacting the association. Kiatmanaroch et al. (2015) also show a significant connection between Gulf crude oil and Malaysian palm oil price series. A recent study by Priyati and Tyers (2016) contends that, since palm oil is a consumption substitute for vegetable oils that can be used as fuels, the energy market plays a

[2] By 2020 palm oil could become an 84 million tonne market, representing 45% of the global vegetable oil market (see Priyati and Tyers, 2016).

prominent role in prompting palm oil prices. Sanders et al. (2014), on the other hand, show that variations in energy prices do not influence palm oil prices. In fact, the authors report a significant association between palm oil and soybean oil markets. Thus, the results of existing studies appear to be somewhat mixed.

It is also worth mentioning that the links between crude oil and palm oil markets receive very little attention. This is a huge void in the literature, considering the economic implications of energy prices on the production of palm oil. It is well documented that oil market uncertainty has a substantial impact on agricultural commodity prices. Harri et al. (2009) demonstrate the impact of crude oil on corn and soybean markets. The findings of Nazlioglu and Soytas (2012) show that food prices are determined by oil price fluctuations. More recently, Ji et al. (2018) show that the oil and gas sector sends volatility to maize, rice, soybean, and wheat markets. Like other agricultural commodities, rising crude oil prices may affect palm oil prices in several ways. For example, variations in oil price are likely to have a significant effect on the production of palm oil due to transportation costs. A recent report from the Energy Information Administration (EIA) reveals that the transportation industry is responsible for 64% of crude oil use. Over the period 1973 to 2012, this sector augmented its usage from 1,022 to 2,326 mtoe (million tons oil equivalent) per year. Given that the cost of transport has a significant impact on the prices of agricultural commodities, the Malaysian palm oil industry could be driven by oil price uncertainty. Recent literature argues that transportation cost plays a crucial role in pricing edible oils including palm oil, soybean oil and other vegetable oils. According to Baumeister and Kilian (2014): '*Agricultural products account for less than 20% of the cost of food to consumers, with the remainder accounted for by the cost of processing, packaging, advertising and transporting food to retail markets*'. The authors add that the cost of transportation plays a major role in determining global food prices. Dillon and Barrent (2016) argue that oil price fluctuations influence the prices of food commodities through the cost of transportation. A study by Mensi et al. (2017) shows that agricultural prices have always been affected by crude oil prices through both input and output costs and that one of these output costs relates to the energy costs of transportation. Ji et al. (2018) state: '*Higher crude oil prices often lead to an increase in agricultural commodity prices through cost-push effects because crude oil represents a major input in the production process*es'. Their study argues that transportation costs are also relevant to cost-push effects because they are affected by energy prices. Overall, as palm oil is an important agricultural commodity, its prices tend to be influenced by energy price variations through output costs including transportation. It is noteworthy that the demand for palm oil, as biodiesel feedstock, upsurges following a growth in crude oil prices, and this in turn raises the price of crude palm oil (Kiatmanaroch et al., 2015). Nevertheless, the associations between these two commodity markets are rarely explored. This paper aims to extend the scant literature.

This paper contributes to the existing literature in several ways. Firstly, in contrast to earlier research, it considers information on the crude oil volatility index (OVX) to be an indicator of oil price risk. Being a forward-looking measure, OVX offers more information than conventional oil prices (Liu et al., 2013). OVX contains both historical volatility information and investor expectation of future market conditions and is thus assumed to be a superior measure of oil price uncertainty (Dutta et al., 2017). Implied volatilities are more accurate measures of the latent volatility process than either ARCH models or realized volatilities. As volatilities are derived from market option prices, they represent the market consensus on the expected future uncertainty (Maghyereh et al., 2016). Hence, this paper contributes to the uncertainty transmission literature by assessing the influence of oil price variance on the Malaysian palm oil sector.

Secondly, the empirical analyses in this paper include the GARCH-jump approach developed by Chan and Maheu (2002). In previous literature, this model is preferred to traditional GARCH models, as it can detect the presence of time-dependent jumps occurring in commodity markets due to natural disaster, recession or political violence (Dutta and Bouri, 2018). Since large movements or jumps in the commodity price index are liable to have thick tails which could exert a significant impact on the value-at-risk (VaR) measure, ignoring such jumps could mislead risk management decisions.

Thirdly, this paper examines the impact of crisis periods on the relationship under investigation. Subsample analyses are conducted to verify whether the impact of OVX on the palm oil sector tends to vary during periods of energy market uncertainty. To this end, the study considers the oil market downturn of July 2014 to December 2015, during which oil prices experienced a sharp decline, and which introduced a number of jumps or spikes in the crude oil volatility index (see Fig.1). This economic stress in the global oil market was the consequence of a strong US dollar, oversupply of crude oil, declining demand and the Iran nuclear deal (Dutta, 2018). To capture the effect of the COVID-19 crisis (Bouri et al., 2020), the sample period is extended from January 2020 to March 2020. These analyses are crucial given that palm oil prices might react differently to changes in oil price volatility during global crisis eras.

Fourthly, we investigate whether there exists a coupling effect between crude oil and biodiesel prices. Given that rising oil prices could cause a growth in biodiesel demand, leading to an upturn in palm oil prices, such an investigation has important implications for policymakers.

Finally, we consider the application of the GARCH-quantile process to explore how the implied volatility of crude oil prices impacts the conditional volatility of the palm oil market under diverse market conditions. Doing so allows us to verify the effect of OVX on the volatility of palm oil prices in low, moderate, and high volatility states. The method is also useful for testing whether the impacts at upper and lower quantiles are equal.

In brief, the findings show that volatile crude oil prices have significant effects on palm oil prices. In particular, increased energy prices lead to higher palm oil prices. This finding is interesting given that in past decades local agricultural prices have not been sensitive to global oil price shocks, as energy prices are determined in international markets rather than domestic markets (Soytas et al., 2009; Nazlioglu, 2011). However, Nazlioglu and Soytas (2012) contend that the past dissociation of these prices does not necessarily assure future detachment. In fact, current literature reveals that local food markets are highly sensitive to global crude oil prices (Tsuji, 2020). Therefore, policymakers should not overlook the impact of oil market volatility when formulating policies related to palm oil prices. However, the cost and implementation of such strategies depends on international energy price movements. Increasing levels of palm oil reserves could limit uncertainty in the edible oil markets. Thus, policymakers should develop specific plans for the stock of crude palm oil, both for producing renewable energies and moderating food price volatility.

2. Materials and methods

2.1. Data

In addition to Malaysian palm oil prices, this study uses the information in OVX to reflect energy market volatility. The sample period spans May 10, 2007 to December 31, 2018. There are 2,931 daily observations in the dataset and the source of the data is Thomson Reuters DataStream. Note that the palm oil prices are expressed in USD.

2.2. GARCH-jump model

The existing literature (Fowowe, 2013; Dutta et al., 2017) suggests that GARCH effects are present in financial time-series data and hence, numerous studies consider the application of GARCH-type models. However, conventional GARCH approaches fail to capture the influence of abnormal information stemming from natural disaster, terrorist attacks, market crashes etc. Chan and Maheu (2002) argue that neither GARCH nor stochastic volatility models can explain the large discrete changes observed in asset returns due to anomalous information. Palm oil prices are sensitive to news or shocks emanating from other financial and commodity markets. For example, a downturn in the global oil market could exert a significant effect on the palm oil industry, as crude oil and palm oil prices usually exhibit a positive association. In order to model the effects of such extreme news or shocks, it is important to incorporate jump approaches into the GARCH specifications to develop GARCH-jump mixture models.

Previous literature suggests that jumps are often observed in commodity prices. Some recent contributions include Dutta et al. (2018), Dutta and Bouri (2018), Zhang et al. (2018), Zhang and Tu (2016), Zhang and Qu (2015), Gronwald (2012), and others. Dutta et al. (2018), for example, show that US ethanol prices are characterized by time-varying jumps. Zhang et al. (2018) report the existence of jumps in the Brent crude oil price index. Zhang and Tu (2016) and Zhang and Qu (2015) document the same. Gronwald (2012) finds that WTI oil prices also experience time-dependent jumps.

In line with previous studies, the following GARCH-jump model is estimated[3]:

$$R_t = \eta + \chi R_{t-1} + \psi \Delta OVX_t + \epsilon_t \tag{1}$$

[3] The AR(1) model for the mean equation is selected on the basis of AIC value.

In this model, R_t signifies the logarithmic returns for the Malaysian palm oil index at time *t*, ΔOVX_t indicates the first order difference for OVX at time *t* and ϵ_t consists of two noises:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \tag{2}$$

with ϵ_{1t} following a GARCH (1,1) process defined as:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1} \tag{3}$$

while ϵ_{2t} denotes a jump innovation given as:

$$\epsilon_{2t} = \sum_{l=1}^{n_t} U_{tl} - \theta \lambda_t \tag{4}$$

In equation (4), U_{tl} gauges the jump size, which conforms to a Gaussian density function having mean θ and variance d^2. The number of jumps, denoted by n_t, follows a Poisson probability function with the time-varying process:

$$\lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1} \tag{5}$$

The above specification is called the jump intensity model with $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$.

Next, the log-likelihood takes the form:

$$L(\Omega) = \sum_{t=1}^{T} \log f(R_t | I_{t-1}; \Omega)$$

where $\Omega = (\eta, \chi, \psi, \omega, \alpha, \beta, \theta, d, \lambda_0, \rho, \gamma)$.

2.3. Testing the asymmetric impact of crude oil volatility

This section investigates whether an asymmetric connection occurs between OVX and the palm oil sector. Such an investigation is crucial as food prices often behave asymmetrically with changes in oil market volatility (Dutta and Bouri, 2018). The presence of a symmetric impact would enable the palm oil industry to properly measure the risk emanating from the oil market, while managing such a risk could be difficult when the effect of oil price volatility is nonlinear. As increases and decreases in energy prices might cause cyclical fluctuations in investments, exploring the asymmetric impact of oil volatility shocks on the palm oil price index is of paramount importance.

To investigate the asymmetric relationship between the markets under study, the following mean equation is estimated:

$$R_t = \eta + \chi R_{t-1} + \psi_1 \Delta OVX_t^+ + \psi_2 \Delta OVX_t^- + \epsilon_t \tag{6}$$

where $\Delta OVX_t^+ = \max(\Delta OVX_t, 0)$ and $\Delta OVX_t^- = \min(\Delta OVX_t, 0)$ refer to positive and negative oil volatility shocks. To examine the presence of asymmetric associations, it suffices to test $H_0: \psi_1 = \psi_2$.

2.4. Additional tests

2.4.1. Coupling effects between crude oil and biodiesel prices

There could be a coupling effect between crude oil and biodiesel prices, which in turn impacts palm oil prices in Malaysia. Specifically, rising oil prices could cause a growth in biodiesel demand, leading to an upturn in palm oil prices. In order to observe such a phenomenon, the following mean equation is considered:

$$R_t = \eta + \chi R_{t-1} + \pi_1 R_{WTI,t} + \pi_2 R_{Biodiesel,t} + \epsilon_t \tag{7}$$

where $R_{WTI,t}$ denotes the log-return for the WTI crude oil price at time *t* and $R_{Biodiesel,t}$ is the same for the EU biodiesel price. Now, since crude oil and biodiesel prices (measured in US dollars) have a high positive correlation, orthogonalized returns on the biodiesel market are considered. To this end, a two-step procedure is adopted. In the first step, the returns on biodiesel prices are regressed on crude oil returns to gauge the impact of the crude oil market on the biodiesel market. In the second step, the residuals are estimated in order to control for the effects of oil shocks on biodiesel returns, using equation (7), replacing $R_{Biodiesel,t}$ with residual series.

2.4.2. Testing for the effect of the currency market

Several researchers (e.g., Akram, 2009; Nazlioglu and Soytas, 2012; Kiatmanaroch and Sriboonchitt, 2014) find that variations in the dollar index have substantial effects on world food prices. Nazlioglu and Soytas (2012) argue that being the leading international currency, the US dominates the worldwide commodity trade. Kiatmanaroch and Sriboonchitt (2014) report that, as various edible oils are beginning to use the dollar exchange rate for international trade, fluctuations in the dollar index have recently shown more volatility, in addition to a depreciation trend, which has a significant impact on these commodities. In line with previous literature, this paper estimates the following regression model to address the effect of OVX after controlling for dollar effects:

$$R_t = \eta + \chi R_{t-1} + \varphi_1 OVX_t + \varphi_2 R_{Dollar,t} + \epsilon_t \tag{8}$$

where $R_{Dollar,t}$ denotes the log-return for the dollar index at time *t*.

2.5. GARCH-quantile process

We employ the GARCH-quantile process to the risk transmission relationship between the crude oil and palm oil markets under diverse market conditions. This approach has two phases. In the first, we apply the standard GARCH model to the palm oil return index and extract the GARCH variance series[4]. In the second, we regress this variance series on the crude oil volatility index using a quantile regression (QR).

Based on the model selection criteria (AIC and BIC), we choose the exponential GARCH (EGARCH) model proposed by Nelson (1991). This approach is given by:

$$h_t^2 = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta h_{t-1}^2 \tag{9}$$

where, h_t^2 indicates the conditional variance of palm oil index returns at time t, and α, β are the ARCH and GARCH parameters, respectively. Here, γ refers to the asymmetric term.

Next, we apply the QR process to the conditional variance index retrieved from the EGARCH model. We frame this process as:

$$Q_{CV_t}(\tau | CV_{t-1}, \Delta \mathrm{OV}X_{t-1}) = \varphi(\tau) + \lambda(\tau) CV_{t-1} + \theta(\tau) \Delta \mathrm{OV}X_{t-1} \tag{10}$$

Following Koenkar and Bassett (1978), $Q_{CV_t}(\tau | CV_{t-1}, \Delta \mathrm{OV}X_{t-1})$ signifies the τ conditional quantile of CV_t, the conditional volatility series of the palm oil market at time t. Here, $\varphi(\tau)$ accounts for the unobserved effect in the quantile model and $\Delta \mathrm{OV}X_t$ refers to the first-order difference of OVX at time t.

Now, for a given τ, we estimate equation (10) by minimizing the weighted absolute deviation:

$$arg \min_{\varphi(\tau), \lambda(\tau)+\theta(\tau)} \sum_{t=1}^{T} \rho_\tau \left(CV_t - \varphi(\tau) - \lambda(\tau) CV_{t-1} - \theta(\tau) \Delta \mathrm{OV}X_{t-1} \right) \tag{11}$$

where, $\rho_\tau(u) = u(\tau - I(u < 0))$ with $\mathrm{I}(\cdot)$ being the indication function.

[4] Unreported results show evidence of a significant ARCH effect in palm oil returns, suggesting the suitability of applying GARCH-based models.

A positive and statistically significant $\theta(\tau)$ indicates that an increase in oil price volatility leads to an upturn in the conditional volatility of palm oil prices. However, if $\theta(\tau)$ is negative, there is an inverse relationship between these markets. We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). Note that the lower quantiles (i.e. 0.05, 0.10, 0.30) represent low volatility states, whereas higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states.

3. Empirical findings and discussion

3.1. Descriptive statistics and unit root tests

Table 1(a) gives the summary statistics for both series considered in this paper. It can be seen from these numbers that palm oil returns are negatively skewed, while OVX exhibits positive skewness. Both series are leptokurtic. We note that none of the series follow the normality assumption as suggested by the results of the Jarque-Bera test. The application of the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests further shows that the first differences of both series appear to be stationary.

Table 1(b) shows the results of the unit root test proposed by Narayan, Liu and Westerlund (2016) (NLW). This test is particularly important as it accounts for structural breaks and conditional heteroscedasticity. In line with ADF and PP tests, the findings of Table 1(b) suggest that both palm oil returns and ΔOVX are stationary. Note that all the detected breaks are associated with important international shocks such as the 2008 global financial shock and the crude oil market downturn in 2014-2015.

Fig.1, which depicts these time-series indexes, shows that fluctuations in edible and energy prices are consistent in both upward and downward directions, which makes the linkage between these markets an interesting topic for further research. Note that OVX data are plotted along with the

WTI index, showing an inverse relationship between these two time-series. For example, during the 2008 turmoil period, a significant fall is observed in WTI index and OVX increased substantially (Ji and Fan, 2016).

3.2. Results of GARCH-jump approach

The findings of the GARCH-jump model, shown in Table 2, suggest that the GARCH parameter (β) is highly significant, confirming the incidence of ARCH and GARCH effects in Malaysian palm oil prices. Moreover, the large value of β reveals that volatility persistence is high for palm oil returns.

Table 2 shows that OVX exerts a significant negative effect on the palm oil market suggesting that increased oil market volatility results in decreased palm oil prices. In other words, OVX and palm oil prices are inversely related. Such a result is not surprising as, when oil market volatility is low, crude oil prices tend to increase which, in turn, causes a growth in palm oil prices[5]. Kiatmanaroch et al. (2015) demonstrate that rising crude oil prices lead to a growth in biodiesel production, causing an upsurge in crude palm oil prices. Hence, oil volatility emerges as a major risk for the edible oil industry and investors and policymakers should be aware of such uncertainty. Overall, the information content of OVX seems important for market participants forecasting future trends in palm oil price series.

The findings in Table 2 show that jump parameters appear to be strongly significant in most cases, revealing the occurrence of jumps, which impact the palm oil price series. Moreover, all the

[5] Dutta (2017) argues that when a drop is observed in OVX, crude oil prices tend to increase.

coefficients of the jump intensity model are statistically different from zero, confirming the presence of time-varying jumps (Fowowe, 2013).

Note that these findings are in line with previous literature. A number of studies document the presence of time-dependent jumps in commodity price indexes. Gronwald (2012), for example, finds such jumps in global crude oil prices. Zhang and Qu (2015), Zhang and Tu (2016) and Zhang et al. (2018) conclude the same. Dutta and Bouri (2018) show that time-dependent jumps occur in the Brazilian ethanol market, and Dutta et al. (2018) reveal that US biofuel prices also exhibit such jump behaviour. Overall, the results of this empirical research demonstrate that time-dependent jumps are common phenomena in the Malaysian palm oil price index and hence modelling these jumps plays an important role in risk management.

3.3. Asymmetric effects of crude oil volatility

The findings of the asymmetric analysis, reported in Table 3, mirror those shown in Table 2. For example, jump parameters appear to be strongly significant. The influence of OVX on the palm oil industry is still negative, suggesting that when oil volatility decreases, the palm oil industry experiences an increase in its price levels. An upturn in oil market volatility, on the other hand, results in a decrease in palm oil prices.

The likelihood ratio (LR) test rejects the null hypothesis of symmetry ($H_0: \psi_1 = \psi_2$). On the basis of this test, it can be concluded that the effect of OVX is asymmetric. Hence, changes (upward and downward shifts) in oil volatility exert a diverse impact on the price levels of this edible oil.

The nonlinear association between oil and palm oil markets has vital implications for researchers and policymakers. For example, the connection encourages academics to adopt nonlinear models instead of linear approaches. Companies functioning in the bioenergy sector should take active measures to hedge oil price risk. To sum up, the asymmetric spillover from energy to palm oil markets should receive special attention while modelling the volatility of palm oil prices.

3.4. Subsample analyses

This section explores the influence of crisis periods on the association between energy market uncertainty and palm oil prices. To serve this purpose, subsample analyses are executed to examine whether the impact of OVX on the palm oil sector tends to vary under diverse market circumstances. To this end, the study uses the period July 2014 to December 2015 which includes the oil market downturn. In addition, to observe the impact of the COVID-19 outbreak, the sample period is extended to cover the period January 2020 to March 2020.

The findings, presented in Table 4, confirm that the effect of OVX is negative. Notably, the magnitude of the impact is higher for the subsample period than the full period. This outcome is not surprising given that OVX reaches a high during the oil market downturn and COVID-19 periods (Bouri et al., 2020). Hence, a major drop in palm oil prices is detected. The subsample analyses further reveal the existence of time-varying jumps in the palm oil price index. Notably, the estimates of the jump intensity parameters $(\lambda_0, \rho, \gamma)$ appear to be higher for the COVID-19 period compared to the full sample period.

3.5. Additional analyses

3.5.1. Coupling effects between crude oil and biodiesel prices

The estimated results of equation (7) are given in Table 5. They suggest that both crude oil and biodiesel markets have a positive effect on the Malaysian palm oil price, implying that an increase in fuel prices leads to an upsurge in biodiesel feedstock prices[6]. This finding is not unexpected, as rising oil prices lift the demand for biodiesel, which in turn causes a growth in palm oil prices. Therefore, the coupling effect of crude oil and biodiesel price is one of the significant factors influencing palm oil prices.

3.5.2. Impact of the currency market

Table 6, which gives estimates of equation (8), confirms that the crude oil volatility index influences Malaysian palm oil prices even after controlling for the impact of the US dollar. However, it is observed that the effect of the dollar on edible oil prices is more pronounced than that of crude oil volatility. This finding is consistent with that documented by Nazlioglu and Soytas (2012). The results suggest a negative association between the dollar and palm oil price indexes. This outcome is in line with Kiatmanaroch and Sriboonchitt (2014) who show that a negative dependence exists between exchange rates and palm oil markets. The empirical findings thus conclude that crude oil volatility and the exchange rate are important factors that determine the behaviour of palm oil prices in Malaysia.

3.6. Risk transmission relationship

So far, we have investigated whether OVX impacts the first-order moment (i.e., mean return) of the palm oil index. It is, however, important for investors and policymakers to understand the risk transmission relationship between energy and palm oil markets. Such investigation plays a crucial

[6] While the findings in Table 2 suggest that the crude oil volatility index (OVX) has a negative effect on palm oil prices, the analysis presented in section 3.5.1 indicates a positive association between the WTI index and palm oil prices. This is due to the fact that OVX and WTI are negatively linked (see Fig.1). Ji and Fan (2016) report a similar connection between the OVX and WTI indexes.

role given that what matters for both market participants and policymakers is not market price variations per se, but their unpredictability and the resultant risks for producers, traders, consumers, and government agents[7]. We, therefore, estimate the risk spillover effects between these two markets. To do this, we employ the GARCH-based quantile regression advocated by Bouri et al. (2019). This method is suitable in the context of our study since it allows us to estimate the risk spillover effect at various quantiles of the dependent variable.

The results of this additional analysis, presented in Panel A of Table 7, reveal that OVX impacts the conditional volatility of palm oil prices only at higher quantiles, implying that the effect of crude oil volatility on palm volatility is significant when the latter is in a high volatility state (see also Fig.2). In other words, crude oil sends volatility to the Malaysian palm oil industry when the market is highly uncertain. It is also noteworthy that such effects become stronger as we move towards the upper quantiles.

Panel B of Table 7 shows the findings of the symmetric quantiles test for changes in OVX. Our objective is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes as the lower quantiles (0.30, 0.10 and 0.05). In particular, we consider the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70) to examine whether the impact of OVX on the volatility of palm oil prices differs for upper and lower quantiles. Our results reveal that the slope parameters do vary for upper and lower quantiles, suggesting that the effects of crude oil volatility shocks tend to vary for low and high volatility periods.

[7] As Dutta (2020) mentions: 'Unpredictable high price volatility can cause additional management costs throughout the supply chain and investment-based processes can be interrupted. Therefore, price volatility is an important concern both at macro level for the government and at the micro level for consumers, producers, and investors'.

These results are important for policymakers given that it is not necessary to formulate strategies for oil market shocks when the palm oil industry behaves normally. However, during extreme volatile periods, policymakers should take effective measures to avoid contagion shocks stemming from the global crude oil market.

3.7. Forecast evaluation

We examine whether including OVX in the GARCH-jump model improves the forecast accuracy for palm oil price volatility. To do so, we consider the following loss functions:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}\left(\sigma_{f,t}^2 - \sigma_{a,t}^2\right)^2 \quad (12)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\sigma_{f,t}^2 - \sigma_{a,t}^2\right| \quad (13)$$

where, MSE and MAE refer to the mean of square error and the mean of absolute error, respectively. Furthermore, T indicates the number of forecast data points, while $\sigma_{a,t}^2$ and $\sigma_{f,t}^2$ are the actual volatility and predicted volatility for day t, respectively. Notably, we consider squared returns as a proxy of volatility. For the one-step ahead forecasts, we estimate the GARCH-jump model for the period 2007 to 2015, and the data for the period 2016 to 2017 are reserved for the out-of-sample forecast analysis. We also employ the Diebold and Mariano (1995) test to evaluate the null hypothesis of no difference in accuracy associated with different models.

The findings are reported in Table 8. They reveal that both MSE and MAE statistics appear to be lower for the proposed GARCH-jump model (with OVX) compared to the baseline model (without OVX). The Diebold and Mariano (1995) test also rejects the null hypothesis at the 1% level, indicating that considering the information content of OVX improves the forecast accuracy for the palm oil price volatility.

3.8. Discussion and implications for sustainability

On the whole, the findings of this empirical study are supported by previous literature suggesting the existence of an information transmission mechanism from world oil prices to Malaysian palm oil prices (Kiatmanaroch and Sriboonchitt, 2014; Nazlioglu and Soytas, 2012; Kiatmanaroch et al., 2015). Notably, our findings are different from the papers cited above in several aspects. Firstly, previous studies show that the risk transmission relationship between energy and palm oil prices is weak, while we show that the linkage is insignificant when the palm oil market is less volatile, but highly significant during periods of high uncertainty. In this regard, we find that the risk spillover effects tend to be stronger as the market becomes more volatile. Hence, the impact of crude oil volatility shocks on the variance of palm oil prices seems to vary depending on the volatility conditions (low, moderate or high). Note that earlier studies investigate the association between these two commodities under average conditions, while we extend the related literature by employing the GARCH quantile regression to examine the association under diverse volatility conditions. Hence, our analysis offers a more comprehensive picture of the association. Therefore, our findings have important implications for investors and policymakers participating in the Malaysian palm oil industry. Secondly, earlier studies (Sanders et al., 2013; Kiatmanaroch and Sriboonchitt, 2014; Nazlioglu and Soytas, 2012; Kiatmanaroch et al., 2015) exploring the association between energy and palm oil prices rely on the conventional prices of the crude oil market and thereby the effect of oil price volatility (e.g., OVX) on palm oil prices remains understudied. A growing body of literature argues that OVX provides more valuable information than traditional oil prices as it is a forward-looking risk measure (Liu et al., 2013; Maghyereh et al., 2016; Dutta et al., 2017). It is thus crucial to consider information on OVX when investigating the impact of oil market volatility on the palm oil market. Thirdly, to the best of our knowledge, this is the first study to test for the coupling effect between crude oil and biodiesel prices, which impact palm oil prices in Malaysia. Specifically, rising oil prices could cause a growth in biodiesel demand, leading to an upturn in palm oil prices. Our findings reveal that the coupling effect of crude oil and biodiesel prices is a significant factor influencing palm oil prices. Fourthly, unlike previous studies, we investigate the impact of oil price volatility on the palm oil index during a period of energy market downturn (2014-2016). Our subsample analyses reveal that, during periods of oil market depression, the impact of energy price volatility on palm oil prices is stronger than that reported for the full period. This finding has important implications, given that during extreme volatile periods policymakers should formulate appropriate strategies to deal with contagion shocks stemming from the global crude oil market. Previous literature finds evidence that the impact of oil price shocks on food commodity prices tends to vary over time. Zhang and Qu (2015), for example, document that before the food crisis period in 2006-2008, agricultural commodity prices remained less sensitive to oil price shocks, while Wang et al. (2014) show that over the post-crisis era, the effects of energy price shocks have been higher than aggregate demand shocks.

It is worth noting that oil prices could affect the agricultural market through two channels. First, oil market fluctuations influence food prices through the costs of transportation and other energy-intensive inputs including fertilizers and pesticides. Second, the upward trend in biofuel production induces a higher derived demand for edible oils which causes the prices of these oils to grow (Chen et al., 2010).

As the results show that palm oil prices react positively to crude oil price changes, increased oil prices would result in higher palm oil prices. While rising palm oil prices boost the income of farmers, they have an adverse impact on consumers due to the rise in commodity and food prices. Therefore, policymakers should not overlook the impact of oil market volatility when formulating policies related to palm oil prices. However, the cost and implementation of such strategies gradually depends on international energy price movements (Zafeiriou et al., 2018). To this end, increasing the levels of palm oil reserves could limit uncertainty in the edible oil markets (Serra and Zilberman, 2013). Thus, policymakers should develop specific plans for the stock of crude palm oil, both for producing renewable energies and moderating food price volatility.

Moreover, palm oil is generally considered a marginal vegetable oil in the global market (Schmidt and Weidema, 2008; Escobar et al., 2014) and in consequential environmental impact studies (macro-level decision support), palm oil is used to compensate for a volume of vegetable oil or animal fat that is being removed from a dedicated market for biofuel (or other) production (Jørgensen et al., 2012; Rajaeifar et al., 2017). However, fluctuations in palm oil prices could bring uncertainties that need to be considered. Therefore, the findings of the current study could be of use for policymaking at the macro level that considers palm oil a marginal product in a dedicated market.

4. Conclusion

Palm oil, which is the one of the most efficient vegetable oil crops in the world, is widely used to produce biodiesel. Biodiesel produces low emissions and noise and is thus an environmentally friendly and sustainable substitute for petroleum diesel. Using biodiesel is highly beneficial as it can either be used directly without major modification in diesel engines or blended with petroleum diesel. Given that palm oil is a cheap feedstock for generating biodiesel, it is one of the main sources of biodiesel production. Malaysia earns a great deal of revenue every year by exporting a huge amount of palm oil all over the world. Therefore, the palm oil industry is very important to the overall economic growth and development of Malaysia. Thus, it is crucial to identify the key factors influencing the price of this edible oil. To this end, the present study investigates how oil price uncertainty impacts the Malaysian palm oil industry.

Employing the GARCH-jump model, it is found that OVX, an indicator of energy price volatility, significantly influences the palm oil price index and, more importantly, this effect is negative suggesting that an upturn in OVX leads to a fall in palm oil prices. Subsample analyses show that the negative impact of energy market uncertainty on palm oil prices intensifies during crisis periods such as the oil market downturn of 2014-2015 and the COVID-19 outbreak. In addition, the effect of OVX is asymmetric, implying that fluctuations (upward and downward shifts) in oil volatility have diverse impacts on the price levels of this edible oil. The findings reveal that palm oil prices experience time-dependent jumps. Considering the coupling effect between crude oil and biodiesel prices, it is found that both markets have a positive effect on the Malaysian palm oil price series implying that an increase in fuel prices leads to an upsurge in biodiesel feedstock prices. Further analyses reveal that the crude oil volatility index influences Malaysian palm oil prices even after controlling for the impact of the US dollar. However, the effect of the dollar on edible oil prices is more pronounced than that of crude oil volatility. Finally, risk significantly transmits from crude oil to the palm oil market during periods of high uncertainty.

The findings of this study have important implications for investors and policymakers participating in the palm oil market. Investors could use the information in OVX for predicting future trends in palm oil prices. Additionally, the information on time-dependent jumps should be considered when estimating market risk. Such knowledge could be beneficial for financiers in making proper investment decisions and reducing portfolio risk.

Policymakers, on the other hand, should take into account the effect of oil market volatility when formulating policies related to palm oil prices. Since the cost and effectiveness of such policies increasingly depend on international energy price movements, it is essential for the policies implemented to aim at limiting the linkages in order for the food crisis to be reduced. To this end, increasing levels of palm oil reserves could limit uncertainty in the edible oil markets. Thus, policymakers should develop specific plans for the stock of crude palm oil, both for producing renewable energies and moderating food price volatility. Since Malaysia is still heavily reliant on fossil energy sources, fluctuations in the petroleum market could be a key obstacle to the country's economic development. Given that developed economies are shifting away from fossil fuels to environmentally friendly alternatives such as biodiesel and similar alternative fuels, the government of Malaysia should take effective measures to promote the export of palm oil which is widely used for biodiesel production. For this purpose, it is important to improve the palm oil futures market in order to accurately gauge market risk.

Our analysis is not free of limitations. For instance, we have not considered the presence of structural breaks in the dataset when examining the impact of OVX on palm oil prices. As such breaks are often observed in commodity markets, ignoring them might mislead the empirical analyses. We use daily data to predict the future volatility of the palm oil price index, while employing intraday high frequency data would be more beneficial for this purpose. Future research could address those two limitations and explore whether the association between crude oil and palm oil is significant at different time scales.

References

Abbott, P.C., Hurt, C., Tyner, W.E., (2008). What's driving food prices? Farm Foundation Issue Report, July 2008.

Abdul-Manan, A.F.N., Baharuddin, A., Chang, L.W. (2014). A detailed survey of the palm and biodiesel industry landscape in Malaysia. Energy, 76:931–41.

Akram, Q.F. (2009). Commodity prices, interest rates and the dollar, Energy Economics, 31, 838-851.

Ashraful, M.M. Rashed, H.K. Imdadul, I.M. Monirul. "Implementation of palm biodiesel based on economic aspects, performance, emission, and wear characteristics", Energy Conversion and Management, 2015

Baumeister, C. and Kilian, L. (2014) Do Oil Price Increases Cause Higher Food Prices? Economic Policy, 80, 691-747.

Borugadda VB, Goud VV. (2012). Biodiesel production from renewable feedstocks: status and opportunities. Renew Sust Energy Rev., 16(7):4763-84.

Bouri, E., Jalkh, N., Roubaud, D. (2019). Commodity volatility shocks and BRIC sovereign risk: A GARCH-quantile approach. Resources Policy, 61, 385-392.

Bouri, E., Demirer, R., Gupta, R., Pierdzioch, C. (2020). Infectious Diseases, Market Uncertainty and Oil Market Volatility. Energies, 13 (16), 4090.

Chan, W.H., Maheu, J.M. (2002). Conditional jump dynamics in stock market returns. Journal of Business and Economic Statistics, 20:377–89.

Chen, S., Kuo, H., Chen, C., (2010). Modeling the relationship between the oil price and global food prices. Appl. Energy 87, 2517–2525.

Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13, 253–263.

Dillon, B.M. and C.B. Barrett. (2016). Global Oil Prices and Local Food Prices: Evidence from East Africa. American Journal of Agricultural Economics 98(1), 154–171.

Dutta, A. (2018). Oil and Energy Sector Stock Markets: An Analysis of Implied Volatility Indexes. Journal of Multinational Financial Management, 44: 61-68.

Dutta, A. (2019). Impact of carbon emission trading on the European Union biodiesel feedstock market. Biomass and Bioenergy, 128, 105328.

Dutta, A. and Bouri, E. (2019). Carbon Emission and Ethanol Markets: Evidence from Brazil. Biofuels, Bioproducts and Biorefining, 13 (3), 458-463.

Dutta, A., Nikkinen, J. and Rothovius, T. (2017). Impact of Oil Price Uncertainty on Middle East and African Stock Markets. Energy, 123: 189-197.

Dutta, A., Bouri, E., Junttila, J., Uddin, G. S. (2018). Does Corn Market Uncertainty Impact the US Ethanol Prices? GCB Bioenergy, 10, 683-693.

Escobar, N., Ribal, J., Clemente, G., Sanjuán, N., (2014). Consequential LCA of two alternative systems for biodiesel consumption in Spain, considering uncertainty. J. Cleaner Prod. 79, 61-73.

Fowowe B. (2013). Jump dynamics in the relationship between oil prices and the stock market: evidence from Nigeria. Energy, 56: 31-8.

Gronwald, M. (2012). A characterization of oil price behavior — evidence from jump models. Energy Economics, 34, 1310–1317.

Gui MM, Lee KT, Bhatia S. (2008). Feasibility of edible oil vs. non-edible oil vs. waste edible oil as biodiesel feedstock. Energy, 33:1646-53.

Harri, A., Nalley, L, and D. Hudson (2009). The Relationship Between Oil, Exchange Rates, and Commodity Prices. Journal of Agricultural and Applied Economics, 41(2009):501–510.

Ji, Q., Bouri, E., Roubaud, D., Shahzad, S.J.H., (2018). Risk spillover between energy and agricultural commodity markets: a dependence-switching CoVaR-copula model. Energy Econ. 75, 14–27.

Ji, Q., Fan, Y., (2016). Modelling the joint dynamics of oil prices and investor fear gauge. Res. Int. Bus. Financ. 37, 242e251.

Johari A, Nyakuma BB, Mohd Nor SH, Mat R, Hashim H, Ahmad A, Zakaria ZY, Abdullah TAT. (2015). The challenges and prospects of palm oil based biodiesel in Malaysia. Energy, 81, 255–61.

Jørgensen, A., Bikker, P., Herrmann, I.T., (2012). Assessing the greenhouse gas emissions from poultry fat biodiesel. J. Cleaner Prod. 24, 85-91.

Kiatmanaroch, T., Puarattanaarunkorn, O., Autchariyapanitkul, K., Sriboonchitta, S. (2015). Volatility Linkages Between Price Returns of Crude Oil and Crude Palm Oil in the ASEAN Region: A Copula Based GARCH Approach. Integrated Uncertainty in Knowledge Modelling and Decision Making. 4th International Symposium, IUKM, pp.428-39.

Kiatmanaroch, T., Sriboonchitta, S. (2014). Relationship between Exchange Rates, Palm Oil Prices, and Crude Oil Prices: A Vine Copula Based GARCH Approach. In: Huynh, V.N., Kreinovich, V., Sriboonchitta, S. (eds.) Modeling Dependence in Econometrics. AISC, vol. 251, pp. 399-413. Springer, Heidelberg.

Koenker, R., Bassett, G., (1978). Regression quantiles. Econometrika: journal of the Econometric Society, 46, 33–50.

Lim, S., Teong, L.K. (2010). Recent trends, opportunities and challenges of biodiesel in Malaysia: an overview. Renew Sust Energy Rev, 14:938-54.

Liu, M.L., Ji, Q., Fan, Y. (2013). How does oil market uncertainty interact with other markets: an empirical analysis of implied volatility index? Energy, 55, 860–68.

Maghyereh, A. I., Awartani, B., & Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. Energy Econ., 57, 78-93.

Misra, R.D., Murthy, M.S., (2011). Blending of additives with biodiesels to improve the cold flow properties, combustion and emission performance in a compression ignition engine—A review. Renew. Sustain. Energy Rev. 15(5), 2413-2422.

Mensi, W., Tiwari, A., Bouri, E., Roubaud, D., Al-Yahyaee, K.H., (2017). The dependence structure across oil, wheat, and corn: a wavelet-based copula approach using implied volatility indexes. Energy Econ. 66, 122–139.

Mosarof, M.H., Kalam, M.A., Masjuki, H.H., Ashraful, A.M., Rashed, M.M., Imdadul, H.K., Monirul, I.M. (2015). Implementation of palm biodiesel based on economic aspects, performance, emission, and wear characteristics. Energy Conversion and Management, 105, 617-629.

MPOB (2018). MPOB. Production of crude Palm oil for 2018.

Narayan, P,K, Liu, R Westerlund, J. (2016), A GARCH model for Testing Market Efficiency, Journal of International Markets, Financial Institutions and Money, 41: 121-138.

Nazlioglu, S., (2011). World oil and agricultural commodity prices: evidence from nonlinear causality. Energy Policy 39, 2935–2943.

Nazlioglu, S., Soytas, U., (2012). Oil price, agricultural commodity prices and the dollar: a panel cointegration and causality analysis. Energy Econ. 34, 1098–1104.

Nelson, D. B., (1991). Conditional heteroskedasticity in asset returns: A new approach, Econometrica 59, 347-370.

Priyati R.Y., Tyers R., (2016). Price relationships in vegetable oil and energy markets. Discussion paper 16.11, The University of Western Australia.

Rajaeifar, M.A., M. Tabatabaei, R. Abdi, A.M. Latifi, F. Saberi, M. Askari, A. Zenouzi, M.J.B.R.J. Ghorbani Attributional and consequential environmental assessment of using waste cooking oil- and poultry fat-based biodiesel blends in urban buses: a real-world operation condition study 4 (2017), pp. 638-653

Sanders DJ, Balagtas JV, Gruere G (2013) Revisiting the Palm oil Boom in South East Asia: Fuel Versus Food Demand Drivers. Applied Economics 46, 127–38.

Schmidt, J.H., Weidema, B.P., (2008). Shift in the marginal supply of vegetable oil. Int. J. Life Cycle Assess. 13, 235.

Serra T, Zilberman D (2013) Biofuel-related price transmission literature: a review. Energy Economics, 37, 141–151.

Soytas, U., Sari, R., Hammoudeh, S., Hacihasanoglu, E., (2009). World oil prices, precious metal prices and macroeconomy in Turkey. Energy Policy 37, 5557–5566.

Thomson Reuters Datastream (2019). Microsoft - time series data. New York: Thomson Reuters.

Tsuji, C. (2020). New evidence on dynamic interactions between biofuel crops, crude oil, and US and European equities—A quinquevariate approach. Fuel, 277: 117765.

Wang, Y., Wu, C., Yang, L., (2014). Oil price shocks and agricultural commodity prices. Energy Econ. 44, 22–35.

Zafeiriou, E., Mallidis, I., Galanopoulos, K. and Arabatzis, G. (2018). Greenhouse gas emissions and economic performance in EU agriculture: An empirical study in a non-linear framework. Sustainability 2018, 10, 3837.

Zhang, C., Qu, X. (2015). The effect of global oil price shocks on China's agricultural commodities. Energy Economics, 51, 354–364.

Zhang, C., Tu, X. (2016). The effect of global oil price shocks on China's metal markets. Energy Policy, 90, 131–139.

Zhang, C.; Shi, X.; Yu, D. (2018). The effect of global oil price shocks on China's precious metals market: A comparative analysis of gold and platinum. J. Clean. Prod. 186, 652–661.

Table 1(a): Descriptive statistics and preliminary tests

Index ↓	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera Test	ADF Test	PP Test
Palm oil returns	-0.0054	0.6935	-0.4600	11.76	9824.49***	37.71 (.00)***	59.00 (.00)***
ΔOVX	0.0081	2.1412	0.4978	26.99	72993.70***	36.82 (.00)***	69.21 (.00)***

Notes: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 1(b): NLW (2016) unit root test

Index ↓	Test statistic	TB1	TB2
Palm oil returns	-12.39*	June-2008	August-2018
ΔOVX	-10.87*	April-2008	October-2014

Notes: TB1 and TB2 indicate the dates of structural breaks. The values of the test statistic are compared with the critical values given in NLW (2016). * indicates statistically significant results at 5% level.

Table 2: Estimates of GARCH-jump model

Variable	Estimate	Standard error	*p*-value
η	.0001	.0088	.33
χ	.0244	.0186	.15
ψ	-.0259***	.0048	.00
ω	.0021	.0014	.12
α	.0080	.0078	.23
β	.9735***	.0183	.00
θ	-.0374	.0447	.39
d^2	.8568***	.1082	.00
λ_0	.0083***	.0032	.00
ρ	.9737***	.0123	.00
γ	.3509***	.0916	.00
Likelihood	-2534.07		

Note: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 3: Testing for asymmetric effects of OVX on palm oil price index

Variable	Estimate	Standard error	*p*-value
η	.0179	.0116	.13
χ	.0182	.0197	.42
ψ_1	-.0357***	.0077	.00
ψ_2	-.0204**	.0087	.02
ω	.0028**	.0011	.01
α	.0124*	.0071	.08
β	.9649***	.0138	.00
θ	-.0647	.0506	.18
d^2	.9117***	.1050	.00
λ_0	.0091**	.0039	.02
ρ	.9660***	.0172	.00
γ	.3572***	.1046	.00
Likelihood	-2396.06		
LR statistic	276.02***		

Note: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 4: Subsample analysis

Variable	Oil market downturn		COVID-19 crisis	
	Estimate	Standard error	Estimate	Standard error
η	.0002	.0069	.1263***	.0330
χ	.0301	.0248	-.0571	.0445
ψ	-.0416***	.0059	-.0588***	.0111
ω	.0017	.0011	.2103***	.0634
α	.0121	.0089	.0212**	.0091
β	.9444***	.0200	.9589***	.0378
θ	-.0429	.0531	-.1148**	.0465
d^2	.9448***	.1249	.8876***	.1099
λ_0	.0091***	.0027	.0295*	.0158
ρ	.9178***	.0229	.9739***	.0149
γ	.3415***	.0895	.6224***	.1880
Likelihood	-1931.41		-925.29	

Note: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 5: Testing for coupling effects of oil and biodiesel prices on palm oil price index

Variable	Estimate	Standard error	*p*-value
η	-2.9236***	.4335	.00
χ	.0304*	.0183	.09
π_1	.0293***	.0043	.00
π_2	.1037***	.0075	.00
ω	.0486***	.0154	.00
α	.0644***	.0165	.00
β	.5009***	.1327	.00
θ	-.0152	.0198	.44
d^2	.6258***	.0501	.00
λ_0	.0051**	.0023	.03
ρ	.9924***	.0031	.00
γ	.2251***	.0492	.00
Likelihood	-2299.15		

Note: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 6: Testing for the impact of the dollar index

Variable	Estimate	Standard error	*p*-value
η	0.0093	.0094	.99
χ	.0155	.0192	.42
φ_1	-.0961***	.0204	.00
φ_2	-.0253***	.0052	.00
ω	.0027**	.0013	.04
α	.0099	.0073	.17
β	.9683***	.0161	.00
θ	-.0570	.0473	.23
d^2	.8818***	.1033	.00
λ_0	.0095**	.0039	.02
ρ	.9680***	.0156	.00
γ	.3675***	.1049	.00
Likelihood	-2385.87		

Note: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 7: Risk spillover from the crude oil to the palm oil market

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: OVX							
Constant	0.0038***	0.0042***	0.0035***	0.0026	0.049***	-0.0014	0.0048
CV_{t-1}	0.8924***	0.8951***	0.9275***	0.9692***	1.0111***	1.1305***	1.1888***
ΔOVX_{t-1}	0.0001	0.0002	0.0005	0.0011**	0.0014**	0.0039***	0.0051***

Panel B: Symmetric quantiles test

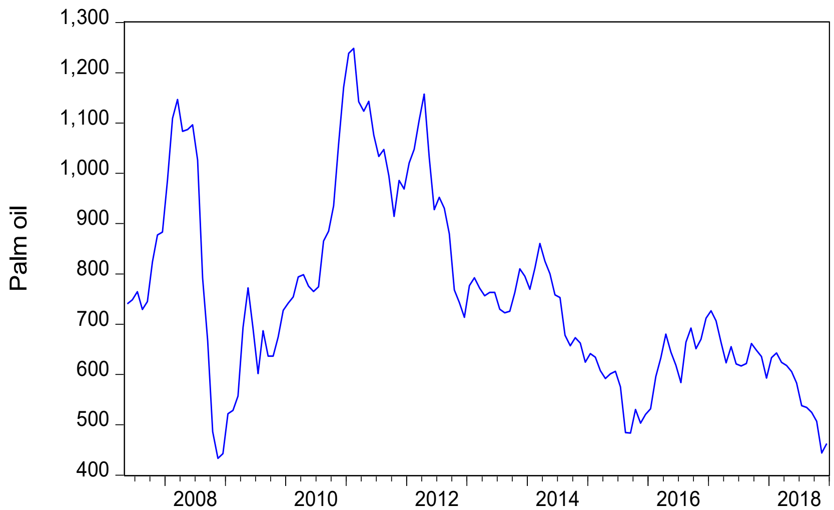
Quantiles ↓	Restricted value	Standard error	p-value	Decision
0.05, 0.95	0.0028	0.0009	0.00	Significant
0.10, 0.90	0.0018	0.0007	0.02	Significant
0.30, 0.70	0.0005	0.0004	0.31	Insignificant

Note: ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

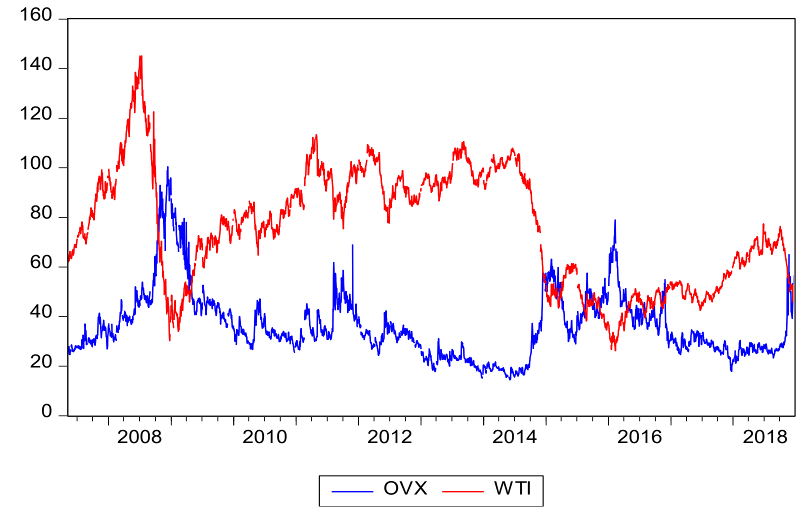
Table 8: Forecast evaluation

	MSE	DM test	MAE	DM test
GARCH-jump without OVX	0.2976	-4.0767***	0.4277	-5.9350***
GARCH-jump with OVX	0.2949		0.4244	

Notes: This table reports the MSE and MAE statistics for forecast evaluation. DM indicates Diebold and Mariano test (1995). ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.



(a)



(b)

Fig.1: (a) Palm oil price index; and (b) OVX & WTI indexes, for the whole sample period

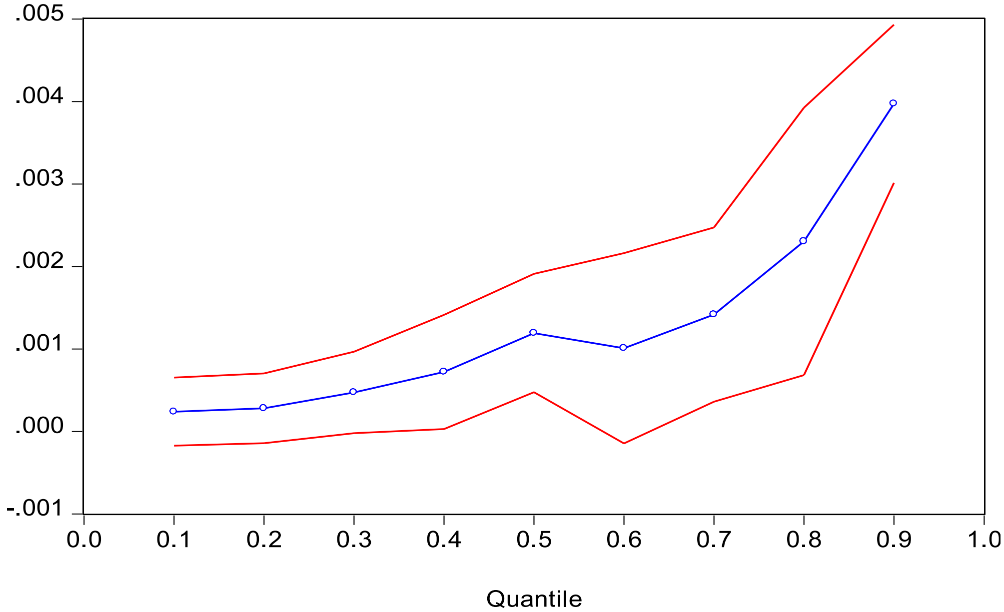


Fig.2: Impact of OVX on palm oil volatility across quantiles