Jurnal Pengurusan 68(2023)
https://doi.org/10.17576/pengurusan-2023-68-01

Energy Futures Price Bubbles and Asset Co-movements with Crude Palm Oil Futures: Through the Lenses of Geopolitical Events and Speculation

(Gelembung Harga dan Pergerakan Bersama Tenaga-Tenaga Pasaran Niagaan ke Depan Bersama Pasaran Niagaan ke Depan Minyak Sawit Mentah: Melalui Peristiwa Geopolitik dan Spekulasi)

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ABSTRACT

The important role played by energy markets has concerned investors regarding the market's behaviour and interconnections when seeking asset diversification strategies, which has become critical in financial analysis. This study aimed to identify price bubbles in energy futures markets and asset co-movements with the crude palm oil futures market (FCPO). This study utilised five futures indices from January 2, 2001, to October 30, 2020. Three methods were employed to explain the behaviour of the energy futures markets: The Generalized Supremum Augmented Dickey-Fuller (GSADF) test, the wavelet power spectrum technique and the wavelet coherence method. The findings from the GSADF test revealed that all energy future markets indicated the presence of asset bubbles, which were influenced by geopolitical events and speculation. The study also demonstrated the presence of periods of high volatility across multiple horizons, which occasionally occurred around the same period as explosive price behaviour. The results of the wavelet coherence method showed that the FCPO market had high co-movement with the Brent crude oil (BRENT) and heating oil (HOIL) markets and, to a lesser extent, with the natural gas (NGAS) and light sweet crude oil (WTI) markets. By linking the GSADF and wavelet approaches, the present study showed how energy price bubbles, their volatility, and co-movements with the FCPO market were related in the presence of geopolitical events and speculation. The present study's findings have suggested strategies regulators and investors can use to manage investment risk and portfolio diversification.

Keywords: Crude palm oil; energy futures; price bubble; wavelet; asset co-movement

ABSTRAK

Peranan penting yang dimainkan oleh pasaran tenaga telah menyebabkan pelabur memberikan perhatian kepada gelagat pasaran dan kesalinghubungan untuk membentuk strategi kepelbagaian aset yang merupakan analisis kewangan yang penting. Kajian ini bertujuan untuk mengenal pasti gelembung harga dan pergerakan bersama tenaga-tenaga pasaran niaga hadapan bersama pasaran niaga hadapan minyak sawit mentah (FCPO). Kajian ini menggunakan lima indeks niaga hadapan yang bermula daripada 2 Januari 2001 hingga 30 Oktober 2020. Tiga kaedah digunakan untuk menerangkan tingkah laku pasaran niaga hadapan tenaga: Ujian Generalized Supremum Augmented Dickey–Fuller (GSADF), teknik wavelet power spectrum dan kaedah wavelet coherence. Hasil kajian dari ujian GSADF menunjukkan semua pasaran tenaga kehadiran gelembung harga yang dipengaruhi oleh peristiwa geopolitik dan spekulasi. Kajian ini juga menunjukkan kehadiran turun naik harga yang tinggi merentasi masa ketika harga sedang ekplosif. Melalui hasil kajian menggunakan wavelet coherence, kajian ini menunjukkan pasaran FCPO mempunyai pergerakan bersama yang tinggi dengan pasaran minyak BRENT (BRENT) mentah dan pasaran minyak panas (HOIL), dan pergerakan bersama yang rendah dengan pasaran gas semula jadi (NGAS) dan pasaran minyak mentah Light Sweet (WTI). Dengan menggabungkan pendekatan GSADF dan wavelet, kajian ini menunjukkan bagaimana gelembung harga pasaran tenaga, ketidaktentuan harga pasaran tenaga, pergerakan bersama pasaran *tenaga bersama FCPO berhubungkait di antara satu sama lain di dalam kewujudan peristiwa geopolitik dan spekulasi. Dapatan kajian ini mencadangkan strategi yang boleh digunakan oleh pihak berkuasa dan pelabur untuk menguruskan risiko pelaburan dan kepelbagaian portfolio pelaburan.*

Kata kunci: Minyak sawit mentah; tenaga niaga hadapan; gelembung harga; wavelet; pergerakan bersama

Received 23 August 2022; Accepted 4 July 2023

INTRODUCTION

Commodities are essential to economic analysis because they impact various markets and market participants. Of the many commodity categories, energy has been shown to impact economies' well-being because it affects the cost of most economic activities. The current trend of energy consumption has received growing attention worldwide, including from industry players and policymakers. The financialisation of the energy market has made investors cognisant of its price movements and potential role in asset diversification strategies. Thus, a thorough understanding of commodity market trends and interconnections has become critical in financial analysis. Furthermore, energy commodity prices appear to have distinct and extreme statistical properties compared with other financial assets. This uniqueness may explain the increasing trend for empirical studies concerning the energy commodity market over the past decade.

As more countries have moved towards implementing improved renewable energy policies, vegetable oil has become an increasingly important biomass energy source. According to Hassan et al. (2020), the global production of oils and fats has expanded rapidly due to; robust GDP growth, rising per capita income, rapid urbanisation, and the expansion of the middle class in major consumer nations. Within this production, palm oil has become the most widely produced vegetable oil worldwide, with steady demand from major consuming nations, such as; China, India, Pakistan, and some African countries. For more than two decades, the world's two major producers of palm oil, Malaysia and Indonesia, have been actively developing the palm oil industry to meet global demand. In 2008, Indonesia became the world's largest producer of palm oil, surpassing Malaysia, and now constitutes more than 50% of global palm oil production (Shigetomi et al. 2020).

In Malaysia, crude palm oil (CPO) is the nation's most significant trading commodity and plays a major role in contributing to Malaysia's GDP growth. Plantations and industries that depend heavily on CPO have devoted a significant portion of their investment to taking positions in the CPO market and offsetting their positions in the CPO futures market (FCPO). A recent trend has shown that a growing number of individual investors and institutional players, such as; fund managers, insurance companies and financial institutions, have been increasingly active in the FCPO market. In the first half of 2020, the FCPO contract volumes on Bursa Malaysia's derivatives market saw a 62% increase compared with the previous year (Kok 2020). The surge in the FCPO market was fuelled by rising uncertainty due to the COVID-19 pandemic, which increased the value of the FCPO market and the derivatives market. This rise in the value of futures markets has been evident in non-renewable energy markets.

Over recent years, the palm oil industry has been scrutinised due to several alleged violations, including; environmental and health issues. The palm oil industry in Indonesia has been linked to several violations, such as; corruption, breach of fundamental human rights, child labour, exploitation of indigenous communities, rainforests deforestation and the destruction of natural habitats (European Parliament 2017). The European Union has been very vocal concerning these issues and has responded to such violations with a ban on importing palm oil. These criticisms have led to bullish sentiments in rival vegetable oil markets, such as; the rapeseed oil market, produced in European Union member countries. Amid the COVID-19 pandemic, thousands of foreign workers were sent back to their home countries when Malaysia entered its lockdowns. Malaysia encountered a worsening labour shortage as foreign workers were restricted from entering Malaysia to contain the spread of COVID-19. This negative outlook in the demand and supply of the palm oil market affected not only its producers and consumers but also its constituent investors. For investors, these uncertainties called for cross-hedging CPO commodities against other assets.

Following this sequence of events, this study used the Generalized Supremum Augmented Dickey-Fuller (GSADF) test to investigate the presence of multiple energy futures price bubbles. This advanced technique allowed nonlinear structures and structural breaks while identifying the presence of bubbles in the markets. The study also used the wavelet approach to examine future volatilities and co-movements between the FCPO market and the other energy futures. Although the study's main interest was co-movements in the FCPO market, the research identified each asset's pricing bubble and volatility to understand the co-movement source. It is also important to mention that the study viewed the FCPO market as an energy market, as CPO is often used as one of the main commodities for producing bioenergy fuels.

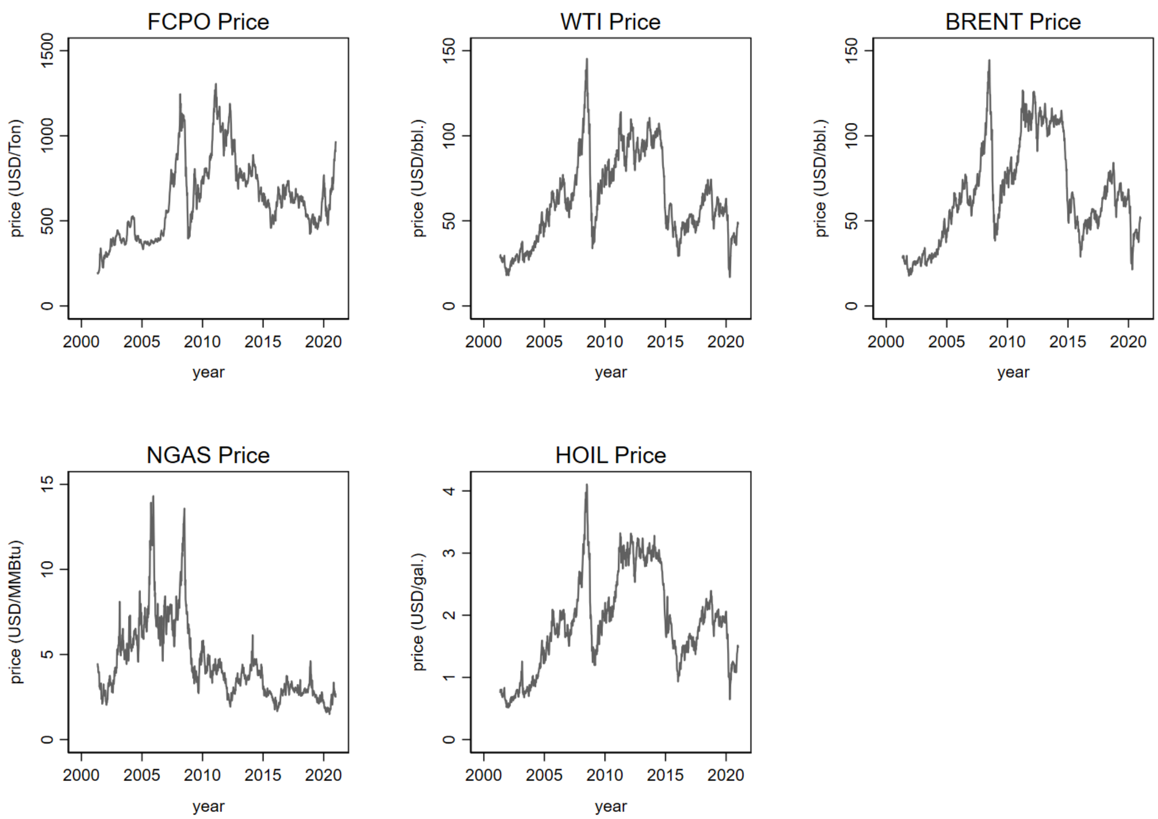

FIGURE 1. Price movements of the FCPO, WTI, BRENT, NGAS and HOIL markets

The present study has contributed to the extant literature concerning this topic in two ways. The present study identified multiple price bubbles in the FCPO market and other energy futures using the GSADF test. Figure 1 shows that all energy futures prices peaked during the Global Financial Crisis (GFC) 2008-2010 period, except for the FCPO market, which peaked in 2011. The rapid increase of FCPO prices has suggested the market for CPO has become more mature as the global demand for biofuel continues to increase. Like other futures markets, the FCPO price decreased in the following years. However, only the FCPO market increased again in 2019, while the remaining futures markets increased slightly later in 2020. Prices in these futures markets have exhibited a range of temporal dynamics and magnitudes of fluctuations. These high price fluctuations suggest the possibility of explosive price movements. These price deviations may demonstrate a unique pattern of FCPO bubbles as a bioenergy fuel relative to non-bioenergy fuels. The samples 2001-2020 dataset contain numerous geopolitical and speculative events that may explain the erratic price behaviour in the energy markets.

The present study further identified the severity of some price bubbles based on the volatilities that formed around the same period as bubble formations using the wavelet power spectrum technique. Secondly, the present study used the wavelet coherence method to demonstrate the asset co-movement of the FCPO and other energy markets. For investors, co-movement determines the cross-hedging opportunity of the FCPO market across time and frequency dimensions. Similarly, policymakers may use co-movements as a sign of market stability and policy coordination across different markets. This indication is crucial for countries such as; Malaysia and Indonesia as exporters of crude oil and CPO.

The novelty of this research lies in linking the empirical findings from the three methods outlined above to explain the behaviour of energy futures markets. The study's importance is derived from identifying the bubbles, their connection to asset volatilities and how they translate into asset co-movement. The emergence of CPO as one of the most traded renewable energy markets has brought a stronger motivation to understand its behaviour in the presence of various speculative and geopolitical events. Failure to do so may cause policymakers to overlook the signals of a potential financial crisis from crude oil markets to the CPO market. In this sense, the producers of CPO are the most affected, followed by investors, particularly CPO traders. The findings of this article have a crucial role in examining potential financial crises and their distortion to the real sector as well as improving policies related to financial stability.

The rest of the article is organised as follows: Section 2 presents the relevant literature review; Section 3 describes the data and methods used in this study; Section 4 discusses the empirical findings. Lastly, Section 5 provides the study's conclusion and policy recommendations.

LITERATURE REVIEW

SPECULATION AND GEOPOLITICAL EVENTS AS THE CAUSE OF PRICE DISRUPTION MECHANISMS IN THE COMMODITY MARKET

Simple microeconomic theory suggests that the law of supply and demand can explain price movements. Like any other goods, the price of energy markets is also determined by these two fundamental factors, *ceteris paribus*. However, price fluctuations in energy markets follow a complex structure, particularly for non-renewable fuels. For instance, Hamilton (2009b) showed that; arbitrary storage, financial futures contracts and the role of commodity futures speculation contributed to the low price elasticity in demand for crude oil. The author also emphasised the depleting supply of crude oil, which has become more relevant with growing demand from the global market.

According to the US Energy Information Administration (2022), crude oil prices have reacted to various geopolitical and economic events, such as; weather and changes in economic growth expectations. Additionally, various political events surrounding the Organization of Petroleum Exporting Countries (OPEC) have disrupted crude oil prices (Hamilton 2009b; Kilian 2009; Su et al. 2017). As a result, non-fundamental factors, such as; geopolitics, speculation, and the US Dollar, have affected oil price movements (Wang & Wu 2012; Zhang & Zhang 2015), which has caused oil prices to deviate from their underlying fundamentals. Thus, any price deviation from oil price fundamentals should be considered a bubble (Stiglitz 1990).

PRICE BUBBLES IN ENERGY MARKETS

Numerous studies have been conducted to investigate price bubbles in energy markets. Floros and Galyfianakis (2020) employed the Supremum Augmented Dickey-Fuller (SADF) test to detect bubbles in BRENT and WTI crude oil prices, with the former index being the benchmark for the latter. Alternately, Su et al. (2017) found multiple explosive bubbles in the WTI crude oil market from 1985 to 2016 using the GSADF test. The authors argued that oil bubbles were formed during periods of high volatility triggered by geopolitical events and speculation. In particular, geopolitical events, such as; wars and political affairs, have triggered short-lived price bubbles (Zhang et al. 2009).

In contrast, speculative events, such as; those that drove crude oil prices upwards before the GFC in 2008, have triggered long-term price bubbles (Hamilton 2009a; Hamilton 2009b). Tsvetanov et al. (2016) also found evidence of oil price bubbles for spot and futures contracts from 1995–2003. Upon further examination, the authors discovered that long-dated contracts (12 months and above) demonstrated longer periods of price bubbles than their short-dated counterparts.

Li et al. (2020) focused on examining price bubbles n the natural gas markets in; the US, Europe and Asia. The authors showed that although price bubbles existed in all three regions, the causes of bubble formations were different. Specifically, price bubbles in the US were caused by price volatility and speculation. In contrast, in Europe, price bubbles were triggered by geopolitical factors. Besides, economic euphoria and oil price fluctuations in Asia were the main contributing factors to its natural gas price bubbles. In another study, Sharma and Escobari (2018) identified multiple episodes of price bubbles in three energy sector indices and five energy sector spot prices. The episodes were consistent across crude oil and its derivatives, whereas the explosive patterns for natural gas prices differed significantly from the rest of the energy market.

Although numerous studies have examined the existence of price bubbles in the energy sector, studies focusing on the renewable energy market remain scant despite its increasing significance. One of the few studies in the existing literature has been presented by El Montasser et al. (2015). They analysed the existence of bubbles in the ethanol-gasoline price ratio in Brazil from 2000 to 2012. The empirical findings revealed two episodes of explosive price behaviour; one formed in 2006, and another emerged in 2010. In a separate study, Adämmer and Bohl (2015) used the momentum threshold autoregressive method to test for speculative bubbles in; wheat, corn and soybean prices in the US. Based on a sample from 2003 to 2013, the results showed speculative bubbles only in wheat prices, whereas the evidence was inconclusive for corn and soybean (both commodities are utilised as biofuel, among other uses).

ASSET CO-MOVEMENTS IN ENERGY MARKETS

Over the last decade, the study of asset co-movements in energy markets has become increasingly popular and extensive. One of the most common research topics in this area has been co-movements between stock and oil markets. For example, Jiang and Yoon (2020) investigated co-movements between oil prices and six stock markets categorised into oil-exporting and oil-importing nations. The study found that the stock markets of oil-importing and oil-exporting countries showed increased co-movement with the oil market in the 16 to 128-week scale using wavelet analysis. In a related study, Wu et al. (2020) demonstrated that the oil price was a major driver in the increased stock market correlation among oil-importing and oil-exporting nations. Thus, oil-exporting and oil-importing nations require a stable crude oil price to avoid extreme stock market fluctuations.

Another popular research trend in academic research has been co-movements between energy and agricultural commodities. As more nations have moved towards adopting clean energy, academicians have become interested in examining how traditional non-renewable energy commodities, such as; oil and gas, have moved with agricultural commodities that produce biofuels. For example, Chiou-Wei et al. (2019) investigated the co-movements of five major commodities (oil, natural gas, soybean, corn and ethanol) using a DCC-MGARCH estimation. The result revealed a high correlation between agricultural commodities (soybean, corn) and ethanol and low co-movements between energy (oil and natural gas) and agricultural commodities. In a similar study, Myers et al. (2014) showed that energy and agricultural prices only co-moved in the short and intermediate time horizons. These co-movements tended to disintegrate in the long-time horizon, as agricultural prices were likely affected by supply conditions and the non-biofuel demand for agricultural feedstocks.

Using the Autoregressive Distributed Lag (ARDL) co-integration approach, Zafeiriou et al. (2018) investigated the bivariate relationships between crude oil and crude oil-soybean futures prices. The empirical results confirmed the interrelationship between crude oil and agricultural commodities used in the production of biofuels. The findings were also consistent with those of Nicola et al. (2016), who demonstrated an increased level of co-movement between energy and agricultural commodities, such as; soybean and maize, which can be used as inputs in the production of biofuels. In China, Liu et al. (2019) offered similar findings whereby 11 of 12 agricultural commodities correlated positively with crude oil prices.

The subject of CPO co-movement with other commodities requires more research. One of the few studies that have examined this topic is the research of Azam et al. (2021). The authors used wavelet analysis to show strong co-movements between the world's major vegetable oil commodities. Further inspection revealed weaker co-movement between CPO and other commodities despite its increasing linkages with soybean and rapeseed oil in recent years. According to Zainudin et al. (2019), Tokyo crude oil was the best alternative for cross-hedging CPO, followed by BRENT crude oil. Alternatively, the authors asserted that NYMEX natural gas was the worst pair for CPO for cross-hedging purposes.

METHOD

DATA

The present study employed five futures indices from January 2, 2001, to October 30, 2020, to examine price bubbles and asset co-movements of the FCPO market with other international energy futures. The five futures indices were: FCPO, WTI, BRENT, NGAS and HOIL. Futures prices incorporate all available data; therefore, they are more effective at identifying supply and demand shocks than spot prices. All data were collected daily from Thomson Reuter's Datastream and Eikon databases. However, the data were converted into monthly frequency before the GSADF analysis to reduce the complexity of the estimation, which reduced the sample size from 4878 to 238 observations. Without such a conversion, a computational estimation was not viable due to the high number of observations. In the wavelet analysis, the daily futures indices were transformed into futures returns by taking the first difference of the natural logarithm to ensure the stationarity of the data.

GENERALIZED SUPREMUM AUGMENTED DICKEY-FULLER (GSADF) TEST

The present study adopted the GSADF test devised by Phillips et al. (2015) to test for price bubbles in futures markets. The GSADF test is a modification of the SADF test initially developed by Phillips and Yu (2011). The SADF test relies on forward recursive regressions, and it is linked to right-tailed ADF unit root tests, which allow for the identification of explosive behaviour in asset prices. As Homm and Breitung (2012) pointed out, the SADF test effectively detects cyclical collapsing behaviour under multiple structural breaks, making it more robust than other tests that portray asset bubbles.

However, due to reduced power and inconsistency, the SADF test fails to identify multiple asset bubbles over a long period (Phillips et al. 2015). Thus, the present study proposed the GSADF method to test for the presence of multiple bubbles by using a backward recursive regression technique to time-stamp asset bubble start and end dates. The recursive right-tailed ADF test in the GSADF test allows changing the start point and the endpoint of the recursion over a sample period. This capability showed the flexibility of the GSADF test over the SADF test in fixing the starting point of the recursion on the first observation. The GSADF test statistic, denoted by $GSADF(r_0)$, is shown as follows:

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [r_2 - r_1]}} \{ADF_{r_1}^{r_2}\}. \quad (1)$$

Equation 1 shows that the GSADF test allowed changes for starting point fraction r_1 from 0 to $r_2 - r_0$ and for endpoint fraction r_2 from r_0 to 1. This implementation provided higher discriminatory power for the GSADF test to identify multiple bubbles within the sample period.

Despite the flexibility advantage, Equation 1 could not reveal the dates for the formation and collapse of bubbles. Hence, the BSADF statistics were constructed and compared with the 95% SADF finite sample critical value sequence. To effectively capture such periodic bubble features, Phillips, Shi and Yu (2015) proposed the BSADF (backward Sup-ADF) test, which has been widely applied in studies related to asset bubbles. Firstly, this study assumed that the sample's endpoint was fixed at r_2T and that the minimum window size was set to r_0T. The BSADF statistics were generated in two phases. The sample's starting point was initially changed backwards from $(r_2 - r_0)T$ to 0. One observation was added for each update, and one ADF statistic was calculated. Secondly, the ADF statistics sequence's supremum was determined, which is:

$$BSADF_{r_2}(r_0) = sup_{r_1 \in [0, r_2 - r_0]}\{ADF_{r_1}^{r_2}\}. \quad (2)$$

Equations 3 and 4 determined the fractions of a bubble's beginning and ending points, respectively:

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{r_2 : BSADF_{r_2}(r_0) > cv_{r_2}^{SADF}\}; \quad (3)$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e, 1]} \{r_2 : BSADF_{r_2}(r_0) < cv_{r_2}^{SADF}\}; \quad (4)$$

where $cv_{r_2}^{SADF}$ represents the critical value of SADF statistics based on a sample size that equals r_2T. As suggested by Phillips et al. (2015), window size r_0 can be determined from sample size T as follows:

$$r_0 = 0.01 + 1.8 / \sqrt{T}. \quad (5)$$

The Akaike Information Criterion (AIC) was selected for automatic lag length selection for unit root testing, with the maximum lag set to eight. The critical values were calculated using a Monte Carlo simulation set to 2,000 replications, as proposed by Phillips et al. (2015).

CONTINUOUS WAVELET TRANSFORM (CWT)

The wavelet transform has a localised basis function in time and frequency spaces, making it an excellent method for analysing nonstationary or transient time series (In & Kim 2012). The CWT of a time series $x(t)$ can be defined as (Ko & Lee 2015):

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\tilde{\psi}_{\tau,s}^{*}(t)dt, \quad s, \tau \in R, s \neq 0, \quad (6)$$

where τ pu is the translation parameter that defines the location of a particular wavelet function in the time series, and scale parameter s considers the degree of the dilation or compression. $\tilde{\psi}_{\tau,s}^{*}(t)$ is the complex conjugate function of $\tilde{\psi}_{\tau,s}(t)$. ψ is the mother wavelet, which can be expressed as:

$$\tilde{\psi}_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad s,\tau \in R, s \neq 0. \tag{7}$$

Wavelets come in several different forms, each with characteristics that make them ideal for various applications. The Morlet wavelet, developed by Goupillaud et al. (1984), was used as the mother wavelet in this analysis as it was suitable for determining the oscillatory components of a signal. Without the scaling function, the Morlet wavelet can be written as (Firouzi & Wang 2019):

$$\psi^{Morlet}(t) = \frac{1}{\pi^{1/4}}e^{i\omega_0 t}e^{-t^2/2}, \tag{8}$$

where t represents normalised time and ω_0 represents frequency.

WAVELET COHERENCE

Given that the purpose of this study was also to identify the relationship between two time series: $x(t)$ and $y(t)$, the cross-wavelet transform was utilised. The cross-wavelet transform was used to find the common power between the time series, allowing the regions where the co-movement of the time series is identified in time-frequency space. The denotations, W_x and W_y, represented the individual wavelet transform for time series $x(t)$ and $y(t)$, respectively. Thus, the cross-wavelet transform can be defined as:

$$W_{xy}(\tau,s) = W_x(\tau,s)W_y^*(\tau,s), \tag{9}$$

where W_y^* is the complex conjugate function of W_y. Based on Equation 9, the local covariance $|W_{x,y}|$ between x and y can be inferred through wavelet coherence. Thus, wavelet coherence can determine the localised correlation and phase relationships between the two nonstationary power time series, x and y (Firouzi & Wang 2019). The wavelet coherence can be written as:

$$R_{xy}(\tau,s) = \frac{|S(W_{xy}(\tau,s))|}{\sqrt{S(|W_x(\tau,s)|^2).S\left(|W_y(\tau,s)|^2\right)}}, \tag{10}$$

where S is a smoothing operator that can be used on time and frequency, and the coherence term R_{xy} equals a value between 0 and 1. A weak correlation is indicated by a coherence value close to 0, whereas a strong correlation is indicated by a value close to unity. Thus, these coherences will determine co-movements between time series x and y.

The wavelet coherence also analysed the phase pattern, which is based on the lag of the oscillations between the two time series, $x = \{x_n\}$ and $y = \{y_n\}$, as a function of frequency. The phase difference denoted by ϕ_{xy} reveals the lead and lag relationships of the time series and the wavelet coherency's positive and negative dependency. The phase difference can be expressed as follows:

$$\phi_{xy} = tan^{-1}\left[\frac{Im\{W_{x_n,y_n}\}}{Re\{W_{x_n,y_n}\}}\right], \phi_{xy} \in [-\pi,\pi], \tag{11}$$

where Im and Re denote the smooth power spectrum's imaginary and real parts, respectively. Directional arrows were used to distinguish different phase patterns in the wavelet coherence map. If *x(t)* and *y(t)* are in phase (antiphase), for example, then the arrow points to the right (left). Similarly, if the arrow points down (or up), then *y(t)* (or *x(t)*) is in the lead.

RESULTS

This study had three objectives: firstly, to investigate the presence of asset bubbles in international energy futures markets; secondly, to examine the volatility of each asset across time and frequency and thirdly, to determine the co-movement of the FCPO market with the rest of the international energy futures markets. The first objective utilised the GSADF method to detect multiple asset bubbles within several futures markets. Then, the study employed the wavelet power spectrum and coherence methods for its second and third objectives, respectively.

PRICE BUBBLES USING THE GSADF METHOD

Table 1 demonstrates the test statistics and the threshold value of the GSADF test. Following the work of Phillips et al. (2015), the window size was set to $r_0 T = 30$, and the window width fraction was $r_0 = 0.01 + 1.8 / \sqrt{T} = 0.1267$. The formation and collapse date of bubbles was identified when the BSADF statistic line crossed the 95% critical value line, as indicated by the yellow-shaded regions. Overall, all energy futures in this study showed sufficient evidence supporting the presence of price bubbles over the sample period.

TABLE 1. Results of the GSADF test for international futures markets

Futures markets	t-statistics
NYMEX Light Sweet Crude Oil (WTI)	2.2641**
ICE Europe Brent Crude Oil (BRENT)	2.3429**
NYMEX Henry Hub Natural Gas (NGAS)	2.4596**
NYMEX NY Harbor ULSD (HOIL)	2.8014***
Bursa Malaysia Futures Crude Palm Oil (FCPO)	4.1122***

*** p<0.01, ** p<0.05, *p<0.1.

Notes: The GSADF test t-statistics were obtained from Equation 1. The corresponding critical values for 90%, 95% and 99% were 1.9031, 2.1279 and 2.6283, respectively.

Figure 2 graphically shows the bubble periods for the five futures markets. The multiple bubbles that existed between September 2004 to September 2006 in the WTI and BRENT markets were influenced by several events. One of the biggest events was the war in Iraq, which disrupted the supply chain of the world's largest oil producer and pushed crude oil prices upward. OPEC's limited spare capacity in oil production and the bankruptcy of Yukos, an oil and gas company based in Moscow, caused the crude oil price to rise. In August 2005, the crude oil price increased considerably when Hurricane Katrina hit the US in the Gulf of Mexico. Prices continued to soar throughout 2006 as rising demand for oil in emerging economies, particularly China, strained the supply-demand balance, with prices averaging 24% higher than the previous year. The combination of these events caused the crude oil price to behave erratically, resulting in several formations of price bubbles during this period.

The bubble that took place from the first quarter of 2008 to the third quarter of 2008 in the WTI and BRENT markets was consistent with the findings of Su et al. (2017). The authors postulated that the bubble was triggered by a speculative event when there was a surge of financial inflows to many commodity markets from other financial markets. The 2008 crude oil bubble finally collapsed when the subprime crisis erupted due to the negative economic outlook, as its price dropped significantly right after reaching its peak in July 2008.

Meanwhile, the sharp price decline in 2015 for the BRENT market can be explained by the over-supply of oil by Middle Eastern countries and the slowing growth of the Chinese economy, as China is the largest oil importer in the world.

The NGAS bubble, which formed in 2005, occurred due to Hurricane Katrina, which disrupted natural gas production for the US in the Gulf of Mexico, driving up natural gas prices. As for the HOIL market, the price experienced five short periods of explosive price behaviour. Since HOIL is a by-product of crude oil, it is unsurprising that most of its price bubbles followed the same trend of bubble formations in the BRENT market.

The first bubble in the FCPO market can be explained by the development of biofuel initiatives by Europe countries, the USA, China, Australia, the Philippines, Indonesia, Malaysia and Thailand. The high price of crude oil, which was more than USD 60 per barrel in 2006, led to a shift towards renewable energy, including palm oil. The increased production of palm methyl ester as part of biodiesel production initiatives led to additional biofuel demand, including palm oil (see Coyle 2007). However, the bubble finally burst in the second half of 2008 due to the GFC. The second FCPO market bubble was caused by the 2015–2016 El Niño phenomenon, which disrupted palm oil production (Kamil & Omar 2017). In November and December of 2018, CPO prices reached their lowest levels in three years due to weak demand from major buyers, such as; China, the EU, Pakistan, and the Philippines.

The asset bubbles in the above commodities mostly coincided with speculation and geopolitical events. The GFC was the most impactful speculative episode, instigating price hikes in various commodity markets, especially in traditional non-renewable energy markets. As crude oil prices increased, investors seeking to diversify their portfolios turned to renewable energy sources, including the CPO market. The CPO market, among other renewable energy markets, such as; the sunflower and rapeseed oil markets, has been a good prospect for investors as the world has become more concerned about global warming issues and has been rapidly moving towards sustainability. Similarly, geopolitical events, such as; wars and natural disasters, have also played their parts in striking supply-demand imbalances in crude oil prices, which eventually spilt over to the commodity markets and stimulated bubble formation.

FIGURE 2. The GSADF tests of the FCPO, WTI, BRENT, NGAS and HOIL market prices. The green line represents the price of futures assets (right axis), the red line represents the 95% critical value sequence (left axis), and the blue line represents the Backwards SADF sequence (left axis).

ASSET VOLATILITY USING THE WAVELET POWER SPECTRUM

Figure 3 illustrates the continuous wavelet power spectrum of the five futures energy markets. The power spectrum is the absolute value of the wavelet transform squared, which measures volatility across the time-frequency domain. The red-coloured regions outlined by a thick black silhouette represent the 95% confidence level determined by Monte Carlo simulations. The cone of influence (COI) divides the plot into reliable (solid-coloured) and unreliable (transparent-coloured) regions. Due to a lack of statistical confidence, regions outside the COI should be disregarded. The power ranges from red (high power) to blue (low power). For reference, this study defined three time horizons: the short horizon from scale 0 to 16, the medium horizon from scale 16 to 256, and the long horizon from 256 onwards.

In general, all assets revealed a higher volatility magnitude on the short horizon and, to a lesser extent, as the horizon increased. Unlike the BRENT market, the WTI market appeared more volatile throughout the study period. This volatility is indicated by the dark red areas (high power) in the WTI market, whereas the BRENT market has a mix of red and yellow areas from a scale of 0 to 16. Additionally, the high volatility in the WTI market tended to last longer on the long horizon, especially at the scale of 512. These high volatilities across multiple frequencies in the WTI market were subjected to US market fundamentals, compared with the BRENT market, which reflected global fundamentals. These underlying differences between the BRENT and WTI markets may have suggested why the BRENT market was much less volatile than the WTI market.

The periods of high volatility in the NGAS market were mostly observable in the medium horizon from 2001 until 2010. However, only one asset bubble existed in the NGAS market, based on Figure 2. The period with the most prominent high volatility was when the bubble collapsed in 2005-2006. That was when Hurricane Katrina hit the US in the Gulf of Mexico, rapidly increasing the NGAS price. As in most assets, the severity of the 2008-2010 GFC materialised in the NGAS and HOIL markets, as shown by the high volatilities in Figure 3. The volatility pattern of the HOIL market followed that of the BRENT market, whereby high volatility periods were observable in 2014-2016 and 2019-2020.

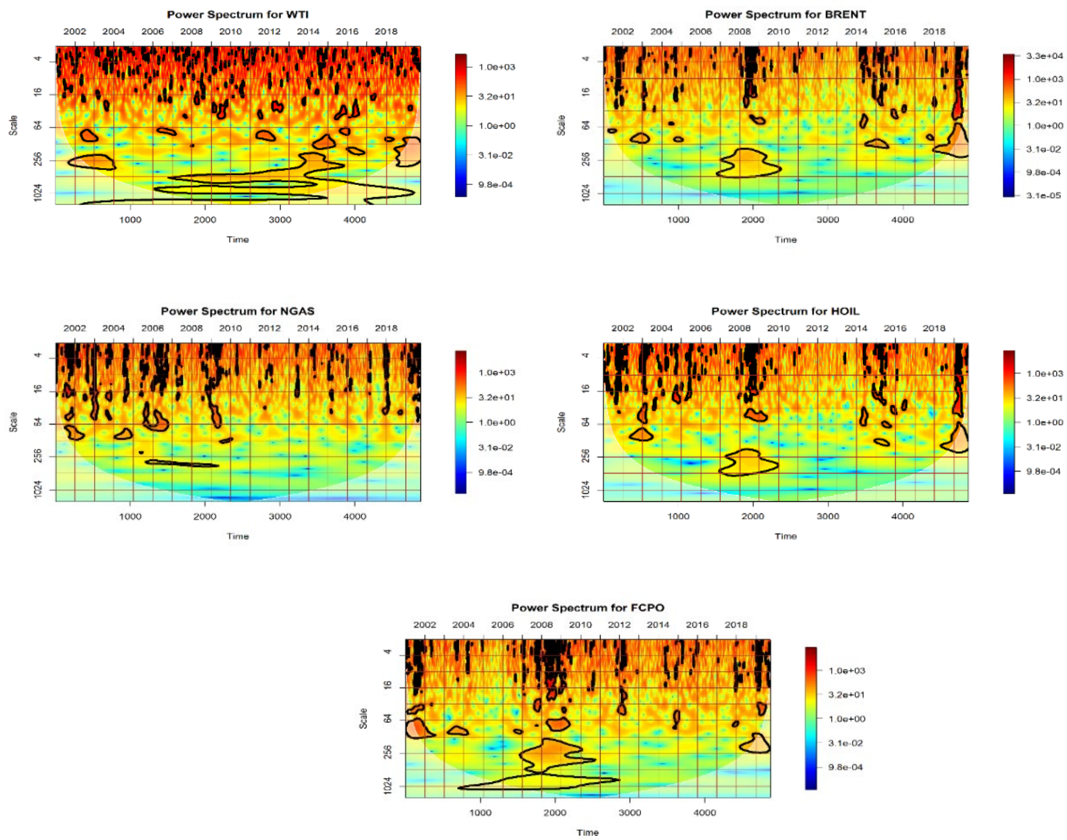

FIGURE 3. Wavelet power spectrum of the FCPO, WTI, BRENT, NGAS and HOIL markets

Based on the power spectrum of the FCPO market, three periods of high volatility occurred on multiple horizons. The first period of high volatility was between 2001-2002, around the short and medium horizons. The second period of high volatility began in 2007 and lasted until 2010 during the GFC period. Although high volatility was observable across all three horizons (short, middle and long), the volatility lasted longer as the time horizon increased. This finding suggested that the GFC's impact on the FCPO market was more severe for long-term than short-term investors.

The third period of high volatility started in 2018 and lasted until 2020, which can be explained by the demand and supply sides of the CPO market. On the demand side, the CPO market has been scrutinised due to negative market sentiment towards the palm oil industry, such as; corruption, violations of fundamental human rights, child labour, exploitation of indigenous communities, rainforest deforestation, and destruction of natural habitats (European Parliament 2017). From the supply side, the COVID-19 pandemic reduced the production of CPO due to lockdowns and labour force shortages.

Simultaneously examining Figures 2 and 3 suggested that an asset bubble could occasionally be present around the same time when the asset tended to be volatile. Such occurrences indicated possible cause-and-effect relationships between asset bubbles and asset volatility. Nevertheless, Sornette, Cauwels, and Smilyanov (2018) postulated that there was no systematic evidence of increasing volatility acting as a diagnostic or early warning signal for the development of a bubble. Volatility does tend to increase at times. However, it frequently decreases before bubbles burst, and volatility rarely changes as the bubble develops toward its end. The present study's findings agreed with this view. However, as some economists may think otherwise, the debate has been left open for further discussion.

ASSET CO-MOVEMENTS USING WAVELET COHERENCE

In this final section, the study investigated co-movements of the FCPO market with the WTI, BRENT, NGAS and HOIL markets utilising the wavelet coherence technique. The technique indicates pair-wise correlations between futures markets across time and frequencies. In wavelet coherence, the hotter (red) colour reflects a greater absolute value of asset co-movement, whereas the thick black silhouette represents a 95% confidence level. The arrows determine the direction of co-movement, in-phase or antiphase, which determines the lead-lag relationship between the assets.

Figure 4 shows that the FCPO market had the highest co-movement with the BRENT and HOIL markets. Given that the BRENT and HOIL markets had similar price bubbles and volatility patterns, both assets reacted similarly to the FCPO market. In particular, higher co-movements were reflected in the medium and long horizons during the GFC. However, co-movement became more extensive beyond the scale of 512, implying the GFC's severity on all three futures markets over the long horizon. Note that co-movements between the FCPO market with the BRENT and HOIL markets were in-phase, as indicated by the rightward-up arrows. Such empirical evidence implied that the BRENT and HOIL markets were good indicators of the FCPO market during the financial crisis. However, they were not reliable to be used as hedging assets for FCPO investors.

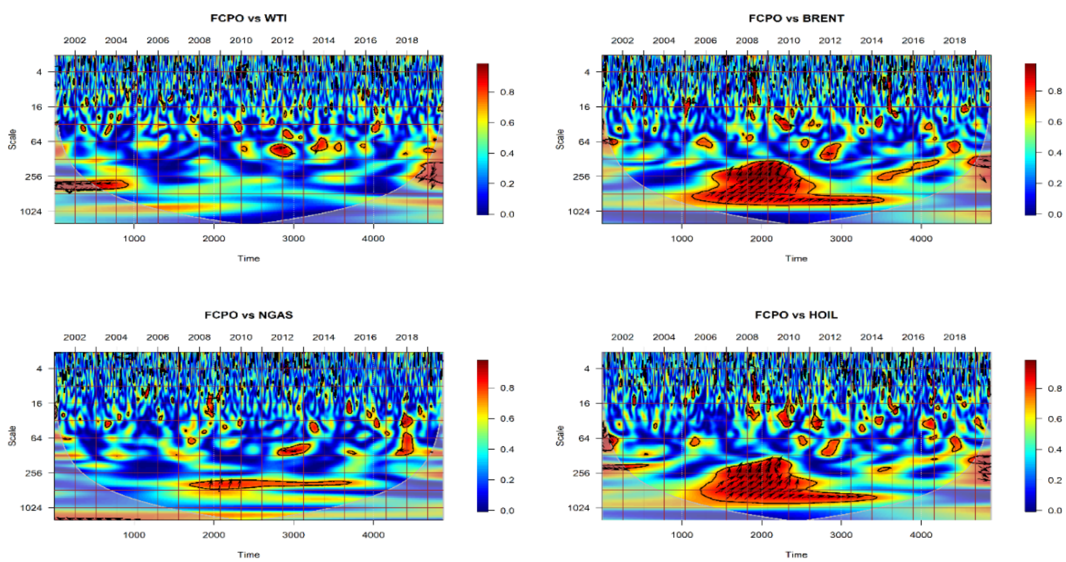

FIGURE 4. Wavelet coherence and phase differences between the FCPO and non-renewable energy futures markets

Alternately, FCPO investors had better hedging opportunities in the WTI markets as the level of co-movements was low and short-lived between 2011-2015. Given that WTI is a crude oil market, such behaviour may reflect the BRENT market, which had the same in-phase co-movement as the FCPO market. This situation shows that the FCPO market was highly correlated with crude oil, which is heavily traded globally (BRENT), compared to WTI. The negative co-movements of the FCPO and NGAS markets in 2012 can be explained by the fall in natural gas prices due to high inventories and rising production, whereas the price of CPO remained high after reaching its peak in 2011. Additionally, the NGAS market showed positive co-movement with the FCPO market during the GFC period, albeit less intense than in the BRENT and HOIL markets.

CONCLUSION

This article had three objectives: (1) to identify the presence of asset bubbles in five energy markets in Bursa Malaysia: FCPO, WTI, BRENT, NGAS and HOIL; (2) to examine the markets' volatilities; and (3) to investigate the co-movement of the FCPO market with the remaining four energy markets across time and frequency domains. The GSADF approach was utilised for the first objective, the wavelet power spectrum for the second and wavelet coherence for the third objective to achieve these tasks. The novelty of this study lies in its linking of the empirical results of the three methods above in explaining the behaviour of the energy futures markets.

For the first objective, the study found that all futures contracts showed the presence of price bubbles from 2001 to 2020. Identifying bubbles in futures markets, which deviate from the fundamental values, could be used as a reference to forecast and anticipate the negative consequences of bubbles. The causal factors of asset bubbles vary in different markets. However, the factors can be classified into speculation and geopolitical events. This study found that speculation and geopolitical events instigated most asset bubble formation. No single asset was more vulnerable towards either speculative or geopolitical events. Another observation was that speculation had demand-oriented disruption on the asset price equilibrium, while geopolitical events had both demand and supply-oriented disruption towards the price equilibrium. Whether these two events can be more or less detrimental than the other has been left for future research.

The second objective revealed that all five energy markets had high volatility between 2007 and 2010. Interestingly, some asset bubbles occurred in the same periods when the markets tended to be volatile. For instance, the first identified bubble in the FCPO market formed in 2007-2008, around the same period as the FCPO market became highly volatile. Thus, the presence of price bubbles may serve as a signal to investors to diversify their holdings. In some cases, explosive price behaviour did not cause the asset to be volatile. Suppose there exists a cause-and-effect relationship between asset bubbles and volatility. In that case, two questions arise: (1) to what extent does an asset bubble cause the asset to become volatile or vice-versa? and (2) does a lead-lag relationship exist between the asset bubble and asset volatility? Again, this study left these questions for future research.

The final objective showed that the FCPO market had higher co-movement with the BRENT and HOIL markets. Theoretically, the present study supported the excess co-movement hypothesis (ECH) between commodity prices (Pindyck & Rotemberg, 1990). The co-movements were more prominent during the GFC period, during which the FCPO market lagged behind the BRENT and HOIL markets. The lag of the FCPO market makes the BRENT and HOIL markets good indicators to determine the performance of the FCPO market, especially when the economy is showing signs of a financial crisis. To a lesser extent, the FCPO market also showed positive co-movements with the NGAS market during the GFC period, with the latter leading the co-movement in the long horizon. However, the FCPO and NGAS markets moved in opposite directions in the medium horizon of 2012-2013 without having any lead-lag relationship. The WTI market proved to be the best asset for hedging opportunities based on its low level of co-movement with the FCPO market throughout the whole period, except for certain short periods, such as; 2003-2004 and 2012-2013.

In conclusion, this research has unravelled the interesting behaviour of energy markets between 2001-2020. As Phillips et al. (2015) argued, identifying asset bubbles can serve as a warning system for investors and policymakers. Unstable energy prices, such as for crude oil, can be detrimental to most countries due to their domino effects on macroeconomic indicators. Given that the use of CPO is not as extensive as crude oil, Malaysia and Indonesia are the most vulnerable countries in periods of explosive CPO price behaviour because they are the two top producers of CPO in the world. Policymakers can observe asset volatility by using the wavelet power spectrum to measure the severity of an asset bubble at different investment horizons. Finally, investors can use the information from wavelet coherence to suggest possible cross-hedging assets for the FCPO market.

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