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International Journal of Energy Economics and Policy

Provided in Cooperation with:

International Journal of Energy Economics and Policy (IJEEP)

Reference: Ngo Thai Hung (2020). Identifying the dynamic connectedness between propane and oil prices : evidence from wavelet analysis. In: International Journal of Energy Economics and Policy 10 (5), S. 315 - 326.

<https://www.econjournals.com/index.php/ijEEP/article/download/9631/5290>.

doi:10.32479/ijEEP.9631.

This Version is available at:

<http://hdl.handle.net/11159/7949>

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Identifying the Dynamic Connectedness between Propane and Oil Prices: Evidence from Wavelet Analysis

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Received: 23 March 2020

Accepted: 20 June 2020

DOI: <https://doi.org/10.32479/ijee.9631>

ABSTRACT

This paper takes into account the LPG markets and aims to examine the short run and long run dependencies between crude oil and propane prices during the period 2006-2018. Our empirical study is based on the wavelet transform approach, which allows us to evaluate the co-movement in both time-frequency spaces. The techniques employed on the dataset includes maximal overlap discrete wavelet transform, wavelet covariance, wavelet correlation, continuous wavelet power spectrum, wavelet coherence and wavelet-based Granger causality tests to measure the intercorrelation between crude oil and propane markets. The findings suggest that the existence of strong interconnectedness between crude oil and propane series in the short and medium run. However, there is a unidirectional impact of propane returns on crude oil markets in the very long term. Furthermore, we construct the wavelet-based Granger causality test at different time scales to provide additional support to our nexus results. Our results provide significant implications for policymakers, portfolio managers, and practitioners who are invited to consider the dynamics of return and volatility spillovers between crude oil and propane markets to create sound policy based on a clear comprehension of the transmission between these markets.

Keywords: Crude Oil, Liquefied Petroleum Gas, Co-movement, Wavelet analysis, Propane

JEL classifications: G13, C22, F30.

1. INTRODUCTION

Propane is by-products of crude oil refining and natural gas processing, which is a part of liquefied petroleum gases (PLG). Nowadays, PLG plays a prominent role in the global energy market and would be used for divergent purposes, such as heating, cooking, and serving as an underlying petrochemical feedstock. As per Oglend et al. (2015), PLG, together with other natural gas liquids, has a significant role in the current US shale gas boom. Changes in gas prices in recent years have made pure natural gas operations less profitable. The connectedness between propane, crude oil, and natural gas supply is dictated by chemistry and technology, and so has been somewhat significant over time. One vital part of the dialogue with regard to the short-run correlation between crude oil prices and PLG prices is the speed and magnitude of product prices response to changes in the oil market (Ederington et al., 2019).

A vast literature on energy markets has been directed towards the nexus between oil and natural gas markets. However, less attention has been paid to other crucial petroleum products and their relations with oil markets. PLG, such as propane, is connected with crude oil prices both on the demand side and supply side. High liquids prices owing to high oil prices, would rise propane production and hence depress propane prices. This implies that the intercorrelation between crude oil and propane prices do not only depend on direct inter-fuel substitution or gas-to-gas prices competition but also the state of the liquid markets (Oglend et al., 2015).

Two main hypotheses in connection with the causal relationship between crude oil prices and PLG have been represented in the literature. The first asserts that the primary association from oil prices to product prices (Asche et al., 2003; Shi et al., 2013), while rests on the hypothesis that the marginal price of a barrel of

a petroleum product may be determined by the highest marginal cost of oil used. Furthermore, causality runs in the opposite direction (Oglend et al., 2013; Bai and Lam, 2019). The direction of causality has significant implications for the policymakers, regulation, and organization of these markets and the facilitation of trade (Acikalin et al. 2018; Al-Sharkas, 2004; Ditimi and Sunday, 2018; Lee and Brahmasure, 2018).

Recently, the vast majority of papers examining the interrelatedness between oil price changes and PLG price changes have taken the direction of causation and said that the dominant channel is from oil prices to product prices (Bai and Lam, 2019). On the other hand, some evidence indicates that causality would run from PLG prices to oil prices (Caporin et al., 2019). Specifically, there is very limited research determining that causal interaction runs from product prices to oil prices as well as the data behavior is measured at a quarterly or more extended frequency (Ederington et al., 2019).

Therefore, the question is whether PLG prices respond more strongly and rapidly to crude oil increases than to oil prices decreases. This study primarily concentrates on the dependence of crude oil markets and propane prices in different locations. It would be beneficial for individual consumers, industrial producers, and consumers, as well as public policymakers and academics, to resort to the frequency domain in order to provide a better understanding of crude oil-PLG co-movement behavior at the frequency level. This study seeks to fill this gap.

Furthermore, crude oil-PLG co-movement has been intensively studied utilizing different empirical methods, but less attention has been paid to the link analysis in the frequency domain. As a consequence, linear and other traditional models are not appropriate for modeling crude oil and PLG price distributions (Bai and Lam, 2019). This paper employs the wavelet approach to analyze the frequency components of the crude oil and propane time series without losing the time information. More precisely, the wavelet transform frameworks allow us to detect oil-propane interactions, which hard to test out using other modern economic time-series models.

To our knowledge and based on a detailed literature review of the most popular academic journal databases, this paper differs in several ways: First, the interaction between the oil price and propane prices in different locations is estimated by using the newly developed technique named Wavelet. In this study, we use maximal overlap discrete wavelet transform, wavelet covariance, wavelet correlation, continuous wavelet power spectrum, wavelet coherence and wavelet-based Granger causality tests to capture the time-frequency co-movements between crude oil and three propane series which adequately obstacles most of the methodological issues that present literature suffers from. Secondly, we investigate the nexus between crude oil prices and propane markets by using the weekly data to analyze instead of using the monthly or annual observation, which is mostly employed in the previous literature. Finally, our findings provide individual consumers, industrial producers, and consumers, as well as public policymakers and academics, with further insights into the international portfolio

and of the links between oil and the PLG market. We find that the unidirectional running from three propane returns to crude oil prices in the long-run and very long-run. In contrast, the strong bidirectional causal connectedness between both variables in the short and medium-run is found.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 represents the methodology and data. Section 4 discusses the empirical results. Lastly, a conclusion is made in Section 5.

2. LITERATURE REVIEW

Prior empirical studies in the interdependence between crude oil and liquefied petroleum gas (PLG) prices produced mixed results with many suggesting the causality differs from location to location and also varies over time. Asche et al. (2003) examine the causal relationship between crude oil and refined prices by employing a multivariate framework. They conclude that the crude price is weakly exogenous and that the spread is constant in the relationship, but the linkages between crude oil prices and some refined product prices imply market integration. Oglend et al. (2015) publish an empirical study on the connectedness between LPG (propane and butane) oil and natural gas prices in the US. Based on cointegration tests, the findings reveal that the PLG-oil relationship is significantly weak in recent years with a move towards cheaper liquids relative to oil, which is in line with developments in the gas sector with increased liquids production. The US natural gas operations are thus unable to rely on high liquids prices to make economic gains automatically. Shi et al. (2013) study the relationship between fluctuations in oil prices and the freight market using a structural vector autoregressive model, provide evidence that crude oil supply innovations have dramatic impacts on the contemporaneous tanker market. Additionally, the paper also interprets that there is a positive relationship between the accumulated responses of the tanker market to crude oil non-supply shocks and crude oil supply shocks. Sun et al. (2014) carry out empirical research on the multiscale correlation between freight rates and oil prices using intrinsic mode function extraction, multiscale component construction and multiscale relevance examined. The paper highlights that tanker freight rates and oil prices show various multiscale properties in terms of the long-run trend, medium-run pattern in low frequency, and short-run fluctuation in high frequency. Specifically, the correlation between the two variables is somewhat high and positive in low frequencies, which suggests that it is crucial and rationale to take into account the dynamic connectedness in multi-scales under the relevant structure. In a same vein, Dahl and Oglend (2016) focus on the changes in the stability of energy prices and provide evidence that in the current regime, oil and natural gas in Europe and the US have become unstable.

More recently, Bai and Lam (2019) investigate both the constant and time-varying conditional dependence dynamics among LPF freight rates, crude oil price, and propane location arbitrage by a conditional copula-GARCH model. The results report that the Baltic PLG freight rate and the arbitrage between propane Far East and the Middle East prices have a significant conditional

time-varying correlation. Furthermore, the paper shows that Middle East propane prices strongly influence crude oil prices in comparison with the Far East and US propane prices. Caporin et al. (2019) analyze returns and volatility spillovers between the S&P 500 index and crude oil, natural gas, ethanol. The paper documents that the connectedness varies according to the trading range among these variables.

With regard to the linkages between freights and commodity prices, Yu et al. (2007) explore the spatial price relatedness in the US and transportation markets using cointegration analysis. The paper provides strong interaction between grain and freight rates in the long run. Similarly, Kavussanos et al. (2014) concentrate on return and volatility spillover effects between various ocean freight and future commodity markets. The main results confirm that the economic nexus tested empirically linkages the derivative price of the commodities transport with the derivative on the freight rate of the vessel transporting it.

With reference to the dependency between crude oil and natural gas prices, Ramberg and Parsons (2012) explore the apparent contradiction of the nexus between crude oil and natural gas prices. They find evidence supporting that natural gas-crude oil relationship is cointegrated and changes over time. Arfaoui (2018) investigates the relationship between spot and futures prices of crude and refined petroleum using the ARDL frameworks. The author points out that the short and long-run elasticities exist between spot and futures prices and between crude and refined oil prices except for gasoline. Lovcha and Perez-Laborda (2020) examine the dynamic volatility relationship between oil, and natural gas using decomposes connectedness measures. Their results show that interaction is typically generated at low-frequencies with volatility innovations across markets having long-lasting influence and provide evidence that the natural gas market was a net transmitter during the research period. la Torre-Torres et al. (2020) shed light on the practical use of Markov-switching models for trading in energy commodity markets, either oil and or natural gas futures. Their findings reveal that with time-fixed variance, the use of the MS Gaussian model results in the best performance in the oil market. However, the authors find no benefit of using trading rule against a buy and hold strategy in the US Treasury bill in the case of natural gas.

When it turns to the wavelet transform frameworks for time-frequency co-movements modeling, Dahir et al. (2018) suggest that the wavelet model is a very powerful estimator that employs signal processing, providing a single opportunity to investigate the co-movements between economic time series in time-frequency dimension. The wavelet approach gives more straightforward insights into potential intercorrelations at various scales along periods. Further, it outperforms the standard OLS regression, ARDL, ECM or VAR, cointegration that are currently the most popular methodologies for examining interdependencies between time series (Hung, 2019). Recently, Raza et al. (2019) study the time-frequency relationship between energy consumption, economic growth, and environmental degradation in the US utilizing the wavelet transform approach. Raza et al. (2018) based on similar approaches to investigate the empirical association of

oil prices with economic activity in the US. The interdependency between the daily returns of major stock markets and foreign exchange rates has also been extensively studied using the wavelet transform framework (Yang et al., 2016; Polanco-Martínez et al. 2018; Aloui and Hkiri, 2014; Dahir et al., 2018). Mishra et al. (2019) also adopt the multiple wavelet analysis to highlight the dynamic linkages between tourism, transportation, growth, and carbon emission in the USA. Tiwari et al. (2018) explore the time-frequency co-movement of and lead-lag connectedness between oil prices and 21 agricultural commodities. Results from wavelet coherency, phase-difference, multiple correlation, and multiple cross-correlations show a high degree of co-movement at a long-run horizon during the research period.

Among all the references mentioned herein, very limited research has been implemented on the propane-oil relationship. Moreover, the most popular often used techniques for interdependence analysis in energy product literature are cointegration tests and ARDL, which do not imply the fundamental time-varying correlation between crude oil and propane series in different locations for different investment horizons. In this paper, we employ the wavelet transform approach providing regions that capture the direction and degree of dependency of the oil and propane returns and expose associations between cause and effect over time and frequency.

3. METHODOLOGY

The wavelet model is a robust estimator that applies signal processing, providing a single chance to investigate co-movements between crude oil prices and propane product prices in the time-frequency dimension. In this paper, we employ wavelet approach in terms of continuous wavelets and cross-wavelet transforms to explore how the local variance and covariance of two-time series make progress, and wavelet coherence and phase analysis to estimate the co-movement correlation between two variables in the time-frequency domain (Reboredo et al., 2017). In addition, discrete wavelets can be used to measure the connectedness between crude oil prices and propane product prices. In this section, we briefly note on wavelet approach.

3.1. Discrete Wavelet Transform

A series $y(t)$ can be decomposed into various time scales as:

$$y(t) = \sum_k s_{J,k} \phi_{J,k}(t) + \sum_k d_{J,k} \psi_{J,k}(t) + \sum_k d_{J-1,k} \psi_{J-1,k}(t) + \dots + \sum_k d_{1,k} \psi_{1,k}(t) \quad (1)$$

Where ϕ and ψ are the father wavelet and mother wavelet functions, denoting the smooth (low frequency) parts of a signal and the detail (high frequency) components. The functions $s_j(t)$ and $d_j(t)$ are the smooth signals and the detail signals, respectively.

Therefore, the time series $y(t)$ can be rewritten as:

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \dots + D_1(t) \quad (2)$$

where the highest-level approximation $S_j(t)$ is the smooth signal, and $D_1(t), D_2(t), \dots, D_j(t)$ are associated with oscillations of lengths 2-4, 4-8, ..., 2^{j+1} , respectively. In our empirical study, we employ monthly data and establish $J = 8$ for multi-resolution level J because past studies have proved that a moderate filter is suitable for financial data (Reboredo et al., 2017).

3.2. The Continuous Wavelet Transform

The continuous wavelet transform $W_x(s)$ allow us to investigate the joint behavior of time series for both frequency and time. The wavelet us defined as:

$$W_x(s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi^*\left(\frac{t}{s}\right) dt \quad (3)$$

where $*$ denotes the complex conjugate and where the scale parameter s identifies whether the wavelet can detect higher or lower components of the series $x(t)$, possible when the admissibility condition yields.

3.3. Wavelet Coherence

To specify the joint behavior of both time and frequency between two time series variables, we employ three specific techniques of wavelet including the wavelet power spectrum, cross-wavelet power and cross-wavelet transform. While the wavelet power spectrum explore contribution to the variance of the series at each time scale, cross-wavelet power measures covariance contribution in the time-frequency space. The cross-wavelet of two series $x(t)$ and $y(t)$ can be defined as:

$$W_n^{XY}(u, s) = W_n^X(u, s) W_n^{Y*}(u, s) \quad (4)$$

where u denotes the position, s is the scale, and $*$ denotes the complex conjugate.

Torrence and Webster (1999) develops the wavelet coherence which can measure the co-movement between two selected time series. The squared wavelet coefficient is defined as:

$$R_n^2(u, s) = \frac{|S(s^{-1} W_n^{XY}(u, s))|^2}{S(s^{-1} |W_n^X(u, s)|^2) S(s^{-1} |W_n^Y(u, s)|^2)} \quad (5)$$

where S is a smoothing parameter for both time and frequency. $R^2(u, s)$ is in the range $0 \leq R^2(u, s) \leq 1$, which is similar to correlation coefficient. If its value is close to zero, evidence of weak interdependence will be determined and vice versa.

3.4. Phase Difference

We cannot shed light on the dichotomy between positive or negative dependency using the wavelet coherence since the coherence

wavelet is squared. Therefore, we use the phase difference tool to examine the dependency and causality interconnections between time series. The phase difference between $x(t)$ and $y(t)$ is defined as follows: (Reboredo et al., 2017).

$$\phi_{XY} = \tan^{-1} \left(\frac{\Im\{S(s^{-1} W_{XY}(u, s))\}}{\Re\{S(s^{-1} W_{XY}(u, s))\}} \right) \quad (6)$$

Where \Im and \Re are the imaginary and real parts of the smooth power spectrum, respectively. Phase interrelatedness between two variables are shown in the coherence phase by means of arrows: (1) the correlation is positive (negative) when the arrows point to the right (left); and the second (first) variable leads the first (second) variable by 90° when the arrows point to down (up).

3.5. Data

We implemented our empirical analysis of intercorrelation and causality between crude oil prices and propane product prices at different time scales using weekly average prices of Brent Crude (OIL), and three propane prices, including Propane Argus Far East Index (PAFEI), Propane CP swap (PCPS) and Propane Mt Belvieu prices (PMB). Our data, spanning the period January 2006-March 2018, were sourced from Baltic Exchange and Datastream. The original data are transformed into the first difference of the natural logarithm ratio by taking the logarithm difference of the two successive weekly prices to compute prices index returns.

Table 1 represents the descriptive statistics of the returns of OIL, PMB, PAFEI, and PCPS indices during the sample period 2006-2018. It is worth noting that the average weekly return series are negative except OIL. Similarly, all four series display negative skewness, while its kurtosis coefficients are positive. Therefore, four concerned variables are far from normally distributed, which means that these indices are fatter tailed. These findings are formally affirmed by the Jarque-Bera test statistics. Additionally, Augmented Dickey-Fuller test rejects the null hypothesis of unit root test for all the return series at the 5% significance level. Finally, statistics from ARCH test for heteroskedasticity reveal that all return series present ARCH effects. These results are thus suitable for further statistical analysis. The graphs in Figure 1 exhibit the price developments of Brent Crude, and three selected propane prices in the whole sample period. It describes a similar fluctuation for the four variables under investigation.

4. EMPIRICAL RESULTS AND DISCUSSION

We use the wavelet transform approach to evaluate the dynamic connectedness between crude oil prices (OIL) and propane prices (PAFEI), (PCPS), (PMB) in different locations.

Table 1: Statistical properties of daily returns over the in-sample period

Variables	Mean	Std.dev.	Skewness	Kurtosis	JB	ADF	ARCH
OIL	0.023048	4.185372	-0.101646	4.791726	81.96769*	-20.34999*	31.34196*
PMB	-0.087830	4.860190	-0.896543	6.717160	429.3593*	-10.62148*	41.63234*
PAFEI	-0.044090	4.162931	-0.483477	6.168709	276.6795*	-18.22874*	26.55984*
PCPS	-0.035252	4.083194	-0.525440	6.906483	412.5334*	-8.140399*	17.58269*

JB and ADF refer to the empirical statistics of the Jarque-Bera test for normality, the augmented Dickey-Fuller unit root tests with an intercept. The ARCH test is used to test the presence of ARCH effect in the datasets. *indicates the null hypothesis rejected at the 1% level

4.1. The Discrete Wavelet Transform (DWT)

In this subsection, we document the results of the DWT of the returns on the variables under examination. In order to assess the degree of energy integration, we use the time-frequency-based wavelet framework to study the various time horizon in the time series. Figure 2 shows the multi-resolution analysis of order $j = 6$ for the selected variables by applying maximal overlap discrete

wavelet transform (MODWT) based on the least asymmetric wavelet filter. The orthogonal component graphs (D_1, D_2, \dots, D_6) are plotted to demonstrate the divergent frequency elements of the original series in detail and a smoothed component (S_6). From Figure 2, we can see that high frequency is found in the short period of the variables under investigation. We further divide these levels into four holding periods, namely, short-run

Figure 1: Time-series of the selected indices

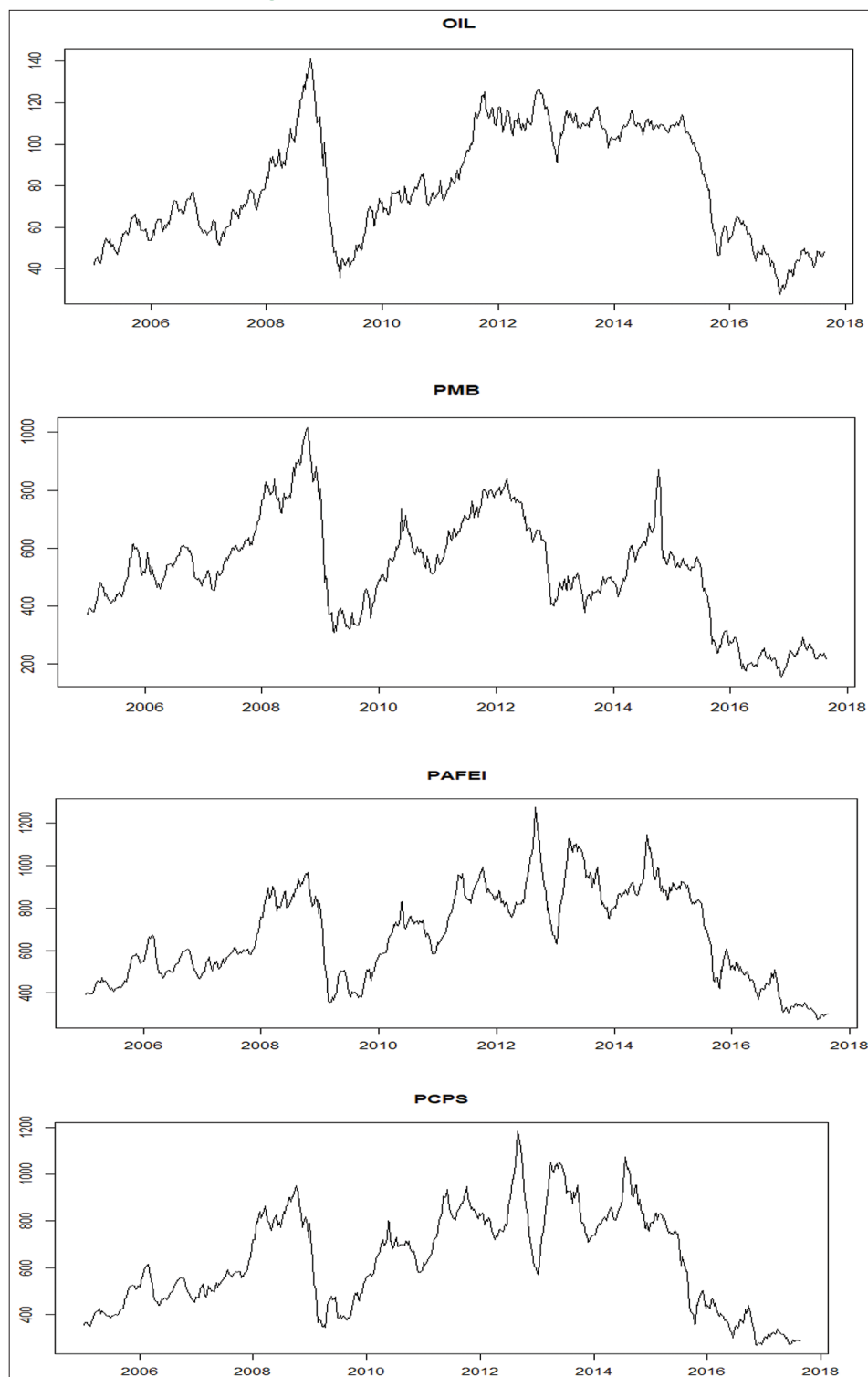
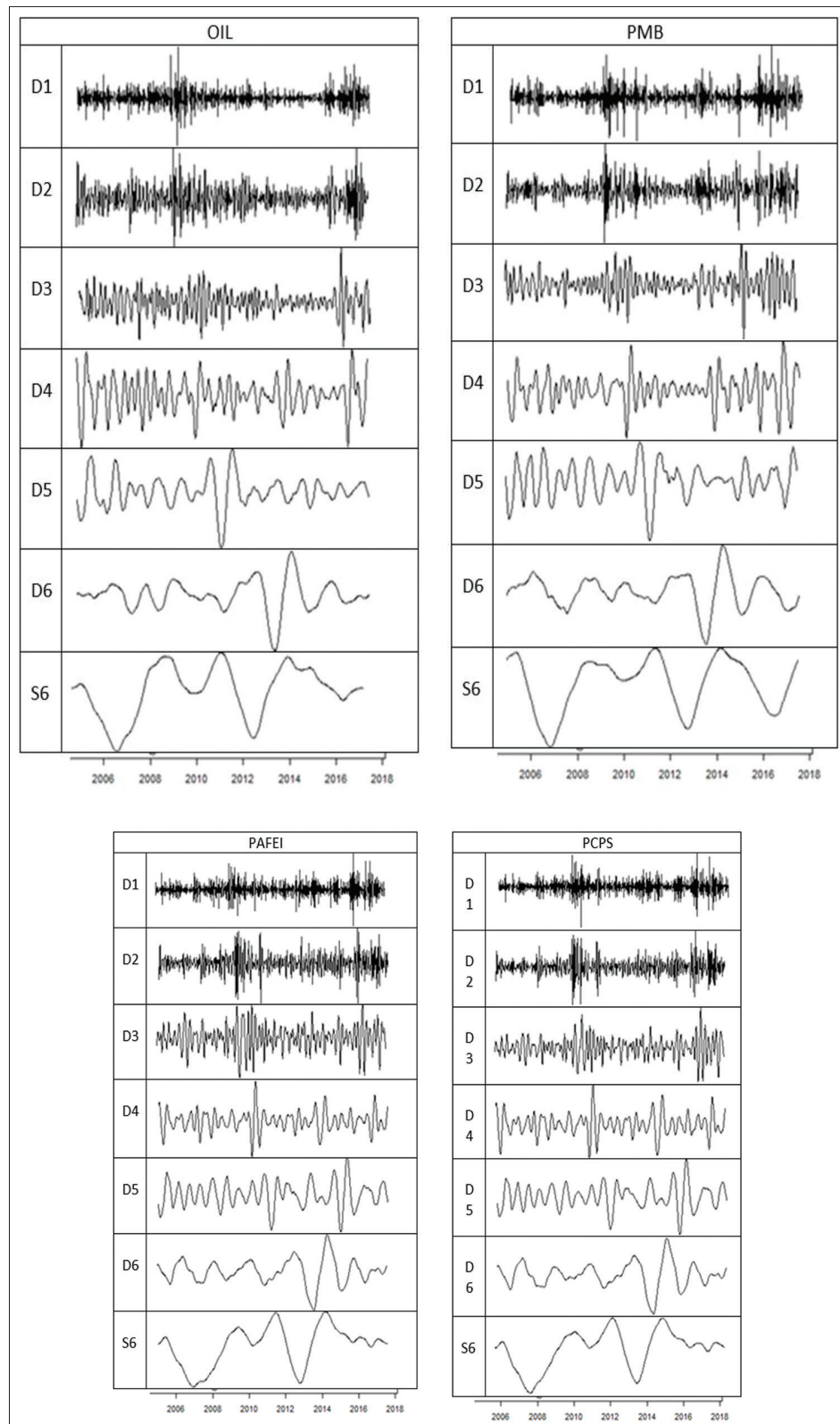


Figure 2: MODWT decomposition of the selected indices on $J = 6$ wavelet level

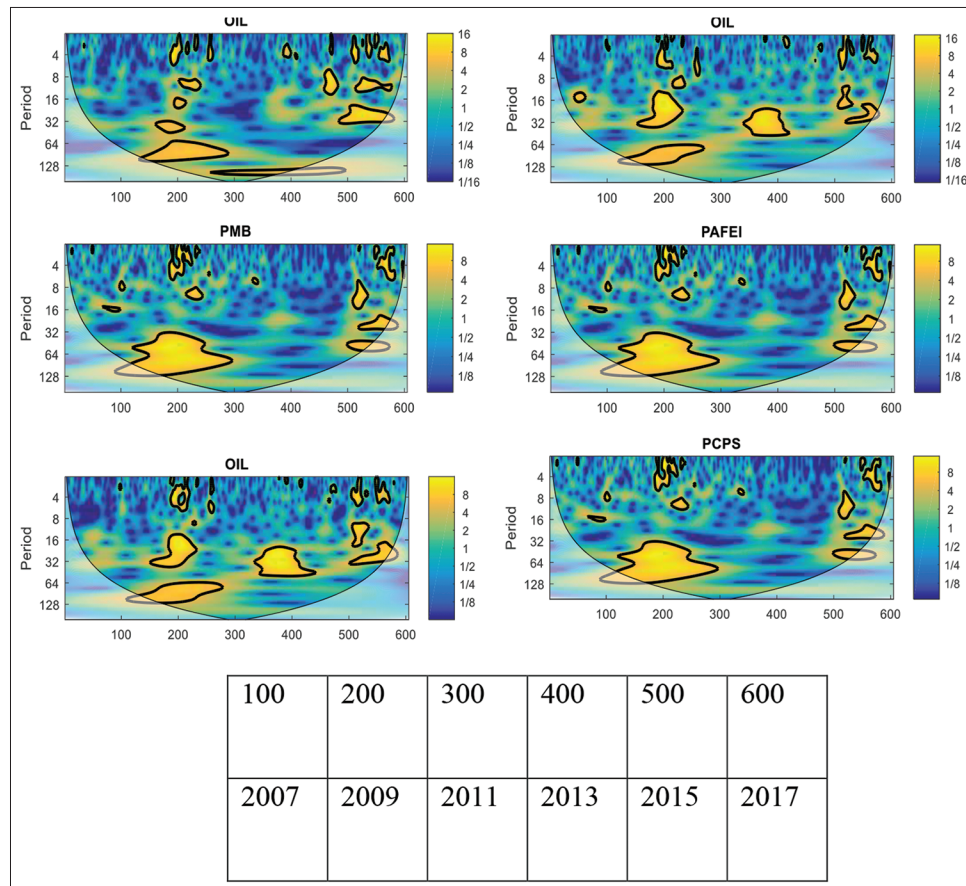
(D_1+D_2) , medium-run (D_3+D_4) , long-run (D_5+D_6) , and very long-run (S_6) .

Variations in the selected variables often occur in the short run. We can observe that these four indexes illustrate the highest variation, at different timescales, around 2009, when the global financial crisis completed.

4.2. Continuous Wavelet Transform (CWT)

Figure 3 reports the raw data variations based on the CWT. The yellow region at the bottom (top) of the continuous power spectra depicts substantial variation at low (high) frequencies while the yellow region on the left-hand side (right-hand) side shows significant variation at the beginning (end) of the sample period,

Figure 3: Continuous wavelet power spectra of OIL, PAFEI, PCPS and PMB. The thick black contour displays the 5% significance level against the yellow noise. The color code for power ranges from blue (low power) to yellow (high power). The vertical axis displays the frequency element, while horizontal axis displays the time element



and areas in blue illustrate weak variation or low intensity between the time series. Put differently, Figure 3 indicates that crude oil prices and propane prices exhibit significant volatility at the 5% significance level. Oil prices show an evolution of variances, revealing high variation at scale (64-128 weeks) around 2010. With regard to the propane indexes (PAFEI, PCPS, PMB), we note high variation and structural changes over the short (2-16 weeks), medium (16-32 weeks), and long term (64-128 weeks) during the period 2007-2010 and 2016-2017. All these outcomes demonstrate that the global financial crisis had a significant effect on crude oil and propane prices.

Cross-wavelet transform (XWT) for the pairs are summarized in Figure 4. XWT is analogous to the CWT plots in Figure 3, the black contour shows 5% significance level. The thin black curved line shows the region affected by edge effects. The XWT reflects the local covariance between OIL and the selected propane returns (PAFEI, PCPS, PMB) at different scales and periods. The XWT reports that the interrelatedness between OIL and propane returns is statistically significant at medium and high frequencies (high scales) using phase arrow, which shows the cause-effect nexus between the selected markets. Arrows pointing right highlight in-phase pairs, such as OIL and PAFEI returns. Arrows pointing left highlight anti-phase pairs such as OIL and PCPS indexes. An arrow pointing straight down means that the right side leads the left side. By contrast, if an arrow points straight up, the left-hand side leads

the right-hand side. Put another way, strong covariance is shown in 64-128-week scales around 2007-2010 and 2016-2017. Therefore, the findings show that the volatility of these indices witnessed underlying changes over the period shown, which means that the energy markets are exposed to long-term volatility. In addition, phase differences suggest that interconnectedness between OIL and the three propane indices is not homogeneous throughout the time and scales, as indicated by arrows that point up, down, right, and left at various times and frequencies.

4.3. Wavelet Coherence

In the section, we examine the co-movements and causal association between OIL and the selected propane returns (PAFEI, PCPS, PMB) using the pairwise plots of wavelet coherence. Figure 5 represents the wavelet coherence power spectrum between these variables. In a similar way to Figure 4, the yellow region at the bottom (top) of the wavelet coherence illustrates strong relationship at low (high) frequencies, while the yellow region on the left-hand (right-hand) side signifies significant relationship at the beginning (end) of the sample period. More precisely, the horizontal axis shows the time component, while the vertical axis shows the frequency components, and color code measures the degree of correlation between pairs of indices. The yellow areas represent that the two series are highly dependent, while blue color areas represent that the two series are less dependent. Additionally, the wavelet coherence effectively performs zones in different time

Figure 4: Cross-wavelet transforms for OIL, PAFEI, PCPS and PMB. The thick black contour displays the 5% significance level against the yellow noise. The color code for power ranges from blue (low power) to yellow (high power). The vertical axis displays the frequency element, while horizontal axis displays the time element. Right up and down presents in-phase, while left up and down presents out-phase

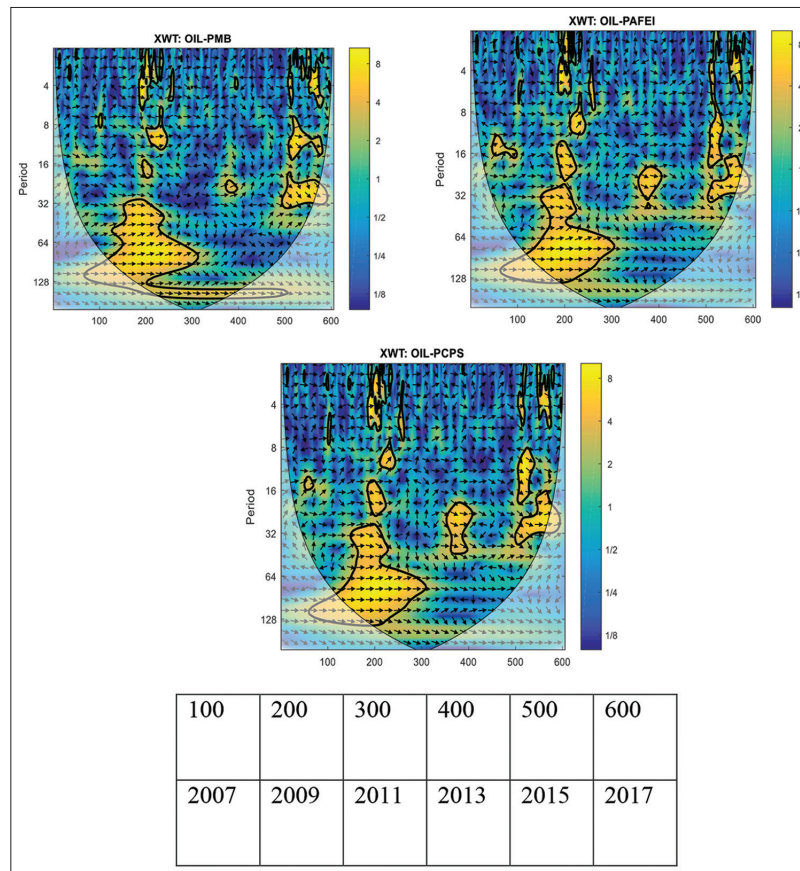
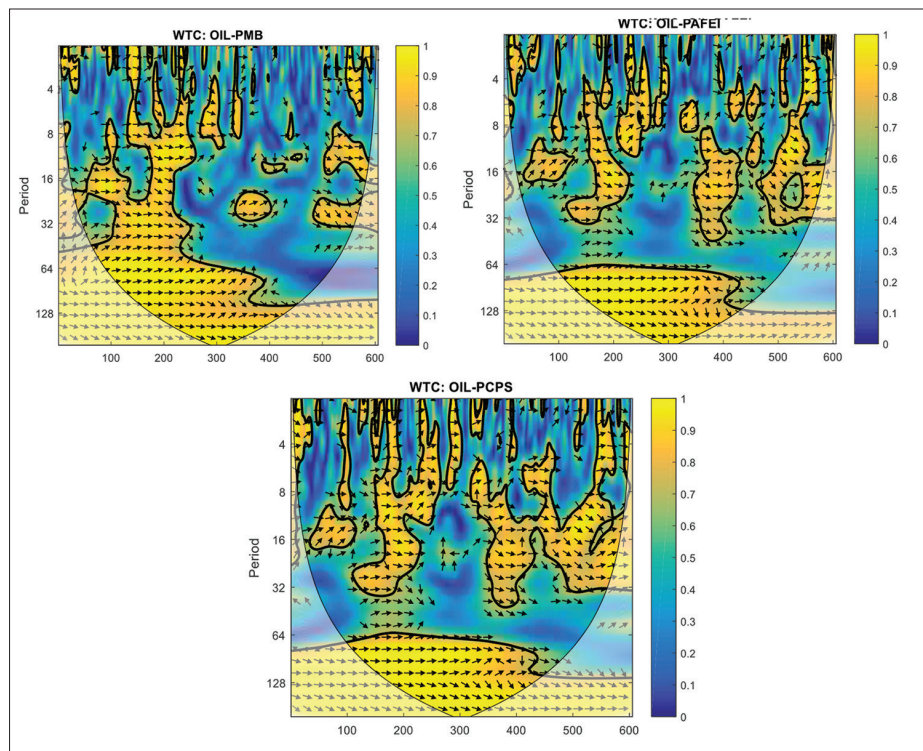


Figure 5: Wavelet coherence of OIL, PAFEI, PCPS and PMB. The thick black contour displays the 5% significance level against the yellow noise. The color code for power ranges from blue (low power) to yellow (high power). The vertical axis displays the frequency element, while horizontal axis displays the time element. Right up and down presents in-phase, while left up and down presents out-phase



and scales where each pair of series is significantly dependent or otherwise, corresponding to the local correlation coefficients spanning from 0 to 1.

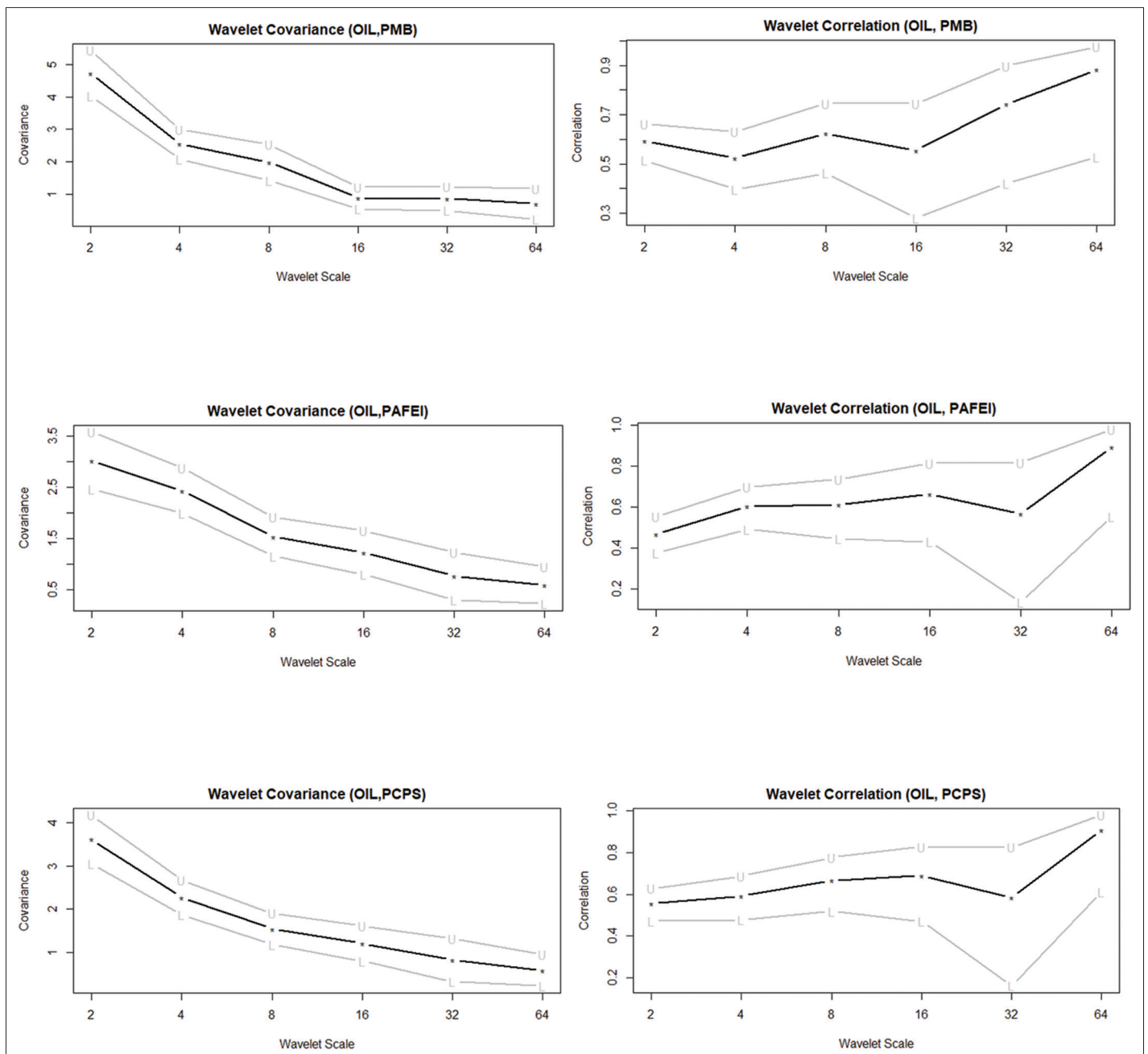
Therefore, wavelet coherence indicates the correlation of index pairs, while the wavelet phase difference finds out the dynamic relationships of variables by observing lead-lag interaction through various investment horizons. Arrows pointing phase differences suggest the intercorrelation direction and cause-effect connectedness. Furthermore, arrows representing the right and left reveal that the paired indexes are in-phase and out-phase, respectively. The in-phase difference indicates that OIL and the propane series PAFEI, PCPS, PMB move jointly in the same direction (positive correlation), while the out-phase wavelet phase

difference shows that the pairs of these returns move in opposite directions (negative correlation) over a specific time and frequency bands. The right-up and left-down arrows suggest that OIL returns, as the dependent variables, are leading, and the right-down and left-up arrows show that the PAFEI, PCPS, PMB returns, as an independent variable, are leading.

We report the results of the wavelet coherence on the bases of four major periods such as short-run (D_1+D_2), medium-run (D_3+D_4), long-run (D_5+D_6) and very long-run (S_6). The findings of the wavelet coherence are summarized in Table 2.

Overall, the wavelet coherence approach result highlights that in the short and medium-run, we have an out-phase situation in

Figure 6: Wavelet covariance and correlation between OIL and propane series. The upper and lower bound are denoted with “U” and “L” respectively at 95% confidence interval. The black dotted line presents the covariance and correlation among the selected series



which OIL is leading (OIL has a causal influence on the propane markets). By contrast, in the long and very long-run, we see an in-phase situation, propane returns are leading (PMB, PCPS, PAFEI have a positive effect on OIL), and an anti-phase situation, OIL are leading (OIL have a causal impact on the propane series). In other words, crude oil prices significantly impact the propane prices, whereas, in the long and very long-run, the propane returns have a positive influence on crude oil prices. Moreover, in the short and medium run, there is a unidirectional influence from OIL to PAFEI, PCPS, and PMB, while in the long and very long run, strong unidirectional causality of the propane prices on the OIL returns is found.

Table 2: Wavelet coherence findings summary

Frequencies	Cross-wavelet coherence
OIL - PAFEI	
Very high frequency	$\uparrow PAFEI \rightarrow \uparrow OIL$
High frequency	$\uparrow OIL \rightarrow \uparrow PAFEI$ $\uparrow PAFEI \rightarrow \uparrow OIL$
Medium frequency	$\uparrow PAFEI \rightarrow \uparrow OIL$ $\uparrow OIL \rightarrow \uparrow PAFEI$
Low frequency	$\uparrow OIL \rightarrow \uparrow PAFEI$ $\uparrow PAFEI \rightarrow \uparrow OIL$
OIL - PCPS	
Very high frequency	$\uparrow PCPS \rightarrow \uparrow OIL$
High frequency	$\uparrow OIL \rightarrow \uparrow PCPS$ $\uparrow PCPS \rightarrow \uparrow OIL$
Medium frequency	$\uparrow OIL \rightarrow PCPS$
Low frequency	$\uparrow OIL \rightarrow \uparrow PCPS$
OIL - PMB	
Very high frequency	$\uparrow PMP \rightarrow \uparrow OIL$
High frequency	$\uparrow PMP \rightarrow \uparrow OIL$ $\uparrow OIL \rightarrow \uparrow PMP$
Medium frequency	$\uparrow PMP \rightarrow \uparrow OIL$
Low frequency	$\uparrow OIL \rightarrow \uparrow PMP$

\uparrow denotes an increase in, \downarrow denotes a decrease in, \rightarrow denotes the variable on the left side of arrow leads the variable on the right side of the arrow

Figure 6 reports the interconnectedness between OIL and PAFEI, PCPS, PMB using MODWT-based wavelet covariance, and correlation analysis, which reveal the interdependence between two variables at different time scales. It is clear from the graph that the positive covariance exists between OIL and three propane series in the short and medium run, whereas negative covariance is found between these pairs in the long and very long term. These findings affirm that OIL positively hit the propane prices in the short and medium run. Similarly, the results of the wavelet correlation between variables are also reported in Figure 6. Overall, the positive and strong correlation between OIL and PAFEI, PCPS, PMB is found in the four periods (short, medium, long, and very term). Hence, we can conclude that the increase in crude oil prices upsurges the propane prices and vice versa. Also, OIL fluctuation is a crucial fundamental element that dramatically raises the propane returns.

In the final step of the analysis, we follow the research of Raza et al. (2018) to implement the Granger causality tests on the wavelet-decomposed data. The results demonstrate that there is a bidirectional causal relationship between OIL and propane returns in the short and medium terms, as indicated in Table 3. In contrast, PAFEI, PCPS, PMB returns have a unidirectional influence on OIL in the long and very long run. In light of this evidence, we can confirm that the co-movements among the model parameters explored through the wavelet coherence framework are subsequently validated by the findings of causality analysis. Hence, we can conclude that there exists a dynamic relationship among variables, and significant causal interaction among variables can be found over the four periods shown.

Our findings, in line with previous papers on dynamic linkages, highlights the existence of liquefied petroleum gas, crude oil, and propane prices. For example, Bai and Lam (2019) document

Table 3: Results of wavelet-based granger causality test at different time scales

Time domain	Result	Null hypothesis			
		Oil does not cause propane prices		Propane prices do not cause oil	
		F-test	P-value	F-test	p-value
OIL - PAFEI					
D ₁ (2-4 W)	$OIL \rightarrow PAFEI$	6.83929	0.0012	0.71696	0.4887
D ₂ (4-8W)	$OIL \rightarrow PAFEI$	6.46189	0.0017	0.34280	0.7099
D ₃ (8-16W)	$OIL \leftrightarrow PAFEI$	4.49754	0.0115	2.44660	0.0875
D ₄ (16-32W)	$OIL \leftrightarrow PAFEI$	2.62115	0.0736	0.71872	0.4878
D ₅ (32-64W)	$PAFEI \rightarrow OIL$	1.32326	0.2670	3.32701	0.0366
D ₆ (64-128W)	$PAFEI \rightarrow OIL$	0.09455	0.9098	1.10065	0.0989
OIL - PMB					
D ₁ (2-4 W)	No causality	2.37370	0.0940	0.09261	0.9116
D ₂ (4-8W)	$OIL \leftrightarrow PMP$	2.26813	0.1000	2.61959	0.0737
D ₃ (8-16W)	$PMP \rightarrow OIL$	1.86626	0.1556	3.16679	0.0428
D ₄ (16-32W)	$PMP \rightarrow OIL$	1.31783	0.2685	3.84780	0.0219
D ₅ (32-64W)	$OIL \leftrightarrow PMP$	13.6992	0.000	13.6992	0.000
D ₆ (64-128W)	$PMP \rightarrow OIL$	0.69233	0.5008	2.0652	0.0341
OIL - PCPS					
D ₁ (2-4 W)	$PCPS \rightarrow OIL$	1.40331	0.2466	2.69674	0.0682
D ₂ (4-8W)	$OIL \rightarrow PCPS$	6.91737	0.0011	2.10841	0.1223
D ₃ (8-16W)	$OIL \leftrightarrow PCPS$	3.35778	0.0355	6.02137	0.0026
D ₄ (16-32W)	$OIL \rightarrow PCPS$	2.59780	0.0753	1.53575	0.2161
D ₅ (32-64W)	$PCPS \rightarrow OIL$	2.19078	0.1127	4.15943	0.0161
D ₆ (64-128W)	$PCPS \rightarrow OIL$	0.27452	0.7600	2.1185	0.0784

that crude oil and propane markets have conditional time-varying dependence, and propane markets are found to have a strong correlation with crude oil prices. Dahl and Oglend (2016) provide evidence that the associations of oil and natural gas prices have become unstable in Europe and the US in the current regime. Oglend et al. (2015) reveal that the shale gas kindly provides a natural experiment to assess the impact of a significant and persistent supply shock on the LPG-oil relationship. Authors also determine that there exists a bidirectional causal association between the Propane, Butane prices, and oil prices. Ramberg and Parsons (2012) have similar outcomes that crude oil and natural gas prices are cointegrated at short investment horizons.

5. CONCLUSION AND RESEARCH IMPLICATIONS

This paper investigates time-frequency connectedness between crude oil prices and propane series in different locations. We have employed MODWT, wavelet covariance, wavelet correlation, continuous wavelet power spectrum, wavelet coherence spectrum, and wavelet-based Granger causality test using the weekly data from the period of 2006 to 2018, which allows us to examine co-movement, volatility and lead-lag interdependency for different investment horizons.

Our empirical results explain the way the relationship between the model parameters varies over time and frequency. The wavelet decomposition approach suggests the frequency of time series becoming in the long term, while wavelet covariance and correlation analysis show a strong positive correlation and relationship between crude oil and three different kinds of propane markets under consideration in the long run. The estimates of continuous wavelet suggest that we observe comparatively a quite stable variance in the long and very long term when compared to short and medium-run and strong variance for very long run scales in all cases of the selected variables.

Moreover, the wavelet coherence indicates high co-movements of crude oil prices and propane series in the medium and long run, which suggests the persistence of strong interrelatedness between these variables. However, in the short term, we observe several various situations of in-phase connectedness, which means that crude oil has a causal impact on three selected propane markets. In the long and very long term, we find the unidirectional influence of three propane series on crude oil returns. Furthermore, the lead-lag relationships between crude oil prices and propane series have mixed results, which suggests that oil markets are strongly influenced by three propane prices in both directions. These results show that lead-lag relationships thus seem to highlight a bidirectional causality at different scales, in particular, in short, and medium-frequency bands of scales during the research period. More importantly, we construct the wavelet-based Granger causality test at different time scales to provide additional support to our connectedness results.

Our empirical results, as shown above, have several important implications. There exist positive links between crude oil markets

and PMB, PCPS, PAFEI prices. This reveals that an increase or decrease in crude oil prices might cause a more considerable rise or drop in the propane markets in three different locations and vice versa. Because propane is often used as a petrochemical feedstock in the petrochemical industry and naphtha exists as its substitute, a dramatic drop in crude oil prices may make naphtha more cost-competitive in comparison with propane, hence further dampens the propane demand in the petrochemical use (Bai and Lam, 2019).

The implications of the economic connectedness are significant on a practical perspective for the design of portfolios, asset pricing, and risk management because they identify the profits of diversification, the growth of asset pricing model, optimal time-varying hedge ratios. Traders would use the indicated associations to build up profitable trading strategies, whereas hedgers are able to observe the commodity futures markets to conduct freight risk management. Policymakers should take into account the dynamics of return and volatility spillovers between crude oil and propane markets to create sound policy based on a clear comprehension of the transmission between these markets. For academics, it opens a new research path to tag on investment opportunities and financing decisions. It then allows for comparison with other markets as well as different future energies that serve as investment instruments.

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