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OIL PRICES AND ECONOMIC GROWTH IN CHINA: A TIME-FREQUENCY ANALYSIS

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ABSTRACT

This study analyzes the inherent evolution dynamics of economic activity and global oil prices in China using the tools of wavelet and wavelet-based VAR-GARCH-BEKK model. Besides, the Wavelet-Granger causality test of Olayeni (2016) provides us further insights into the magnitude and direction of causal connectedness between oil prices and economic activity in China over time and across different frequencies simultaneously. We find that the spillover effects between China's economic activity and global oil prices are time-varying in different time and frequencies in terms of direction and strength. More accurately, the prices and volatility spillovers between them are significant in the short and medium run but eventually neutral toward the long run. The Wavelet-Granger causality provides us further insights into the lead-lag relationships between oil prices and China's economic activity from an economic perspective. The dynamic time-frequency association findings suggest crucial implications that might assist policymakers and other market participants in mitigating risk.

Keywords: wavelet analysis, oil prices, economic activity, VAR-GARCH-BEKK, causality

INTRODUCTION

The dynamic associations between the global oil market and economic activity levels have increasingly been the concentration of extensive research because fluctuations in oil prices have created an unpredictable effect on the international economies (Yu et al., 2019). China has become a net oil importer since 1994. Peng et al. (2020) show that China has become the largest oil-import country in the world since 2016, and the global dependence on China’s oil has been up to 65.4%. The rising international dependence on China’s crude oil sharply intensified the impact of worldwide oil on China's economy.

Over the past couple of decades, China has maintained and established itself as the fastest-growing emerging economies in the world, and China’s economy has been dramatically influenced by the international oil price shocks (Allen et al. 2013; Peng et al. 2020; Hung, 2022b) since the reform and opening up, driving oil demand to increase quickly (Chen, Zhu, & Zhong, 2021). China's crude oil imports have also increased to fulfill local demand, resulting in a very strong link with imports (Chen, Zhu, & Li, 2020). As a result, it is indispensable to look into the causal associations between global oil prices and economic growth in China.

In the existing literature, extensive research examines numerous complexities in the connectedness between oil price shocks and industrial output. However, the present literature results have never reached a consensus and had mixed results in this issue. The nexus between crude oil market and industrial output is carried out by utilizing data sets for different countries (Ahmed et al., 2017; Raza et al., 2018; Herrera et al., 2011; Scholtens and Yurtsever, 2012;

Awartani et al. 2020). Several papers take into account the non-linearity in the nexus between global oil market and industrial output (Yıldırım & Öztürk, 2014; Huang et al., 2005; Mehrara & Sarem, 2009; Sakashita & Yoshizaki, 2016). In the Chinese context, the connections between the oil market and industrial output are examined by (Cross & Nguyen, 2017; Tang et al. 2010; He, 2020; Chen et al., 2021), but the interplay between the global oil market and industrial output as well as the methods used is limitedly discussed (Raza et al., 2018).

Notwithstanding the economic activity influence of the oil price variations, there are two more issues that need to be addressed. Firstly, previous research has focused on the relationship between oil prices and macroeconomic fundamentals, whereas related research on industrial production remains limited (Sakashita & Yoshizaki, 2016). Secondly, the existing literature has primarily utilized in-variant methodologies. Specifically, recent papers have started to conduct the study on the nexus between oil price variations and macroeconomic indicators from the time-varying perspective (Peng et al., 2020; Chen, Zhu & Zhong, 2021; Chen, Zhu, & Li, 2020; Jo et al. 2019; Cross & Nguyen, 2017; Tang et al., 2010; He, 2020; Chen et al., 2020; Raza et al., 2018). These papers have employed either single-country data or multi-country panel data to examine the intercorrelation within the time-domain approach. However, time-varying connectedness between global oil prices and economic activity can change across various frequencies (Hung, 2022a). The true economic link between variables, rather than the conventional aggregated level, would be expected to hold at the scale level, according to Tiwari et al. (2019).

Based on the above deficiencies, we employ a wavelet methodology to look into the dynamic interplay between the global oil market and China's industrial output. Then, the VAR-GARCH-BEKK model is applied to capture the dynamic multiscale associations between international crude oil markets and economic activity in China. Empirically, we employ multiple wavelet approach methods to examine both lead-lag relationship and casual associations in co-movements between variables under consideration. More importantly, in economics, the ability to observe time-series variables spanning both time and frequency may be more appealing than either time or frequency alone, because time series variables are frequently prone to regime shifts, structural breaks, outliers, and clustering (Tiwari et al., 2019; Hung, 2022a). Besides, through using the VAR-GARCH-BEKK models, we provide a deeper investigation of the degree of the price and volatility spillovers and other time-varying effects across the Chinese economic activity and oil prices at different time and frequency domains. Our empirical results conclude that there is the existence of time-varying co-movement and spillover between global oil prices and Chinese economic activity.

Our paper provides three primary contributions. First, the current paper expands the existing literature on the effect of the international oil market on industrial output in China in terms of time-series and frequency-domain analyses. More specifically, related research mainly centers on the connectedness between oil price and economic activity at the original data level in the time domain. Unfortunately, they ignore the relationship at different frequency bands (Chen et al., 2019). Second, in contrast to previous literature that examines the relationships, the time-varying price and volatility spillover effects between the global oil market and economic activity at various time scales are investigated. Because volatility is a measure of risk, identifying the volatility transmissions has significant consequences for policymakers in predicting future market co-movements. Third, our study employs the wavelet cohesion method of Rua (2013) and a novel approach to causality using a time-frequency approach introduced by Olayeni (2016), which may give robust findings. As a result, differing from previous works on oil price and economic activity co-movement, our study provides straightforward insights into global policymakers and risk managers. Traditional approaches do not allow the estimation of continuous changes in the lead-lag nexus between indicators, nor allow for the interrelatedness of short- and long-run investment strategies. Using Olayeni's (2016) approach, we can examine nonlinearities, structural breaks, and different lead-lag scenarios between global oil prices and economic activity in China. Therefore, this research would add to the body of knowledge in the literature on the subject of spillover effects between crude oil prices and economic growth in China over time scales.

LITERATURE REVIEW

Theoretical Linkages

Oil prices can affect economic activity via a variety of transmission channels. First, there is the classic supply-side effect, which states that rising oil prices indicate the reduced availability of a basic input to production, resulting in a decrease in potential output (Hamilton, 1983; Jo, 2014; Yıldırım & Öztürk, 2014). The result is a rise in production costs and a slowing output and productivity growth. Second, increased oil prices result in income transfers from importing to exporting nations. It alters the international trade balance and exchange rates. Net oil importers typically experience a deterioration in their balance of payments, which exerts downward pressure on exchange rates, assuming all other factors remain constant (Cuñado & Gracia, 2003; Eryiğit, 2012). Third, according to the real balance effect, a rise in oil prices would increase the demand for money. There is a rise in interest rates and a deceleration in economic growth as a result of the failure of monetary authorities to meet rising money demand with increased supply. Fourth, higher oil prices have a restrictive effect on the supply side. As oil is an input in the production process, rising input costs result in decreased profits for producers (Lardic & Mignon, 2008). Therefore, decreased investment spending may result from decreased profits. Fifth, an increase in oil prices could have a negative impact on consumption, investment, and stock prices. Consumption is influenced by its positive relationship with disposable income, while investment is affected by rising firm costs. An alternative explanation offered in the literature is that it is the monetary policy response to the oil price shock that reduces economic activity, not the increase in oil prices. Because of these factors, oil prices can have an effect on economic activity. Based on the arguments mentioned above, oil prices significantly impact economic activity across countries. Therefore, we make the following testable hypothesis:

H1: Oil prices have a negative impact on economic activity in China.

Empirical Literature

The literature on the interaction between oil markets and industrial output can be divided into the following two aspects: the divergent case of developing countries and developed countries; and the methodologies used for the analysis of global oil prices and economic activity. The early studies included Hamilton (2011), Hooker (1996), Kilian and Vigfusson (2011), and Santini (1985), all of which documented and explained the nonlinear nexus between oil prices and aggregate economic activity. The negative relationship between oil price uncertainty shock and economic activity has been revealed in many empirical studies (Hamilton, 1983; Jo, 2014; Yıldırım & Öztürk, 2014; Cobo-Reyes & Perez Quiros, 2005; Cuñado and Gracia, 2003; Eryiğit, 2012). Taspinara (2015) confirms that crude oil changes impact Turkey's industrial production, known as a net oil importer country. In the Pakistan context, Ahmed et al. (2017) show that, to some extent, oil price shocks have a negative influence on industrial production. They also put forward that this association is used to predict oil future prices that can assist in taking precautionary steps to control economic activity.

About how crude oil prices interact with economic activity in the non-linear relationship is as follows. Huang et al. (2005) use the multivariate threshold model to examine the influence of crude oil price shocks on economic activity in the US, Canada, and Japan and find that the oil price change or its variation has a limited influence on the economies. Mehrara and Sarem (2009) report on the effects of oil price shocks on industrial production in three oil-exporting countries (Indonesia, Saudi Arabia, and Iran), concluding that the causal relationship between the oil market and economic activity in these countries is significant when asymmetric methods are used. Herrera et al. (2011) carry out the three leading techniques of asymmetric and possibly non-linear feedback from the oil prices to the US industrial production and find that the non-linear model is most robust for samples starting before 1973. Yıldırım and Öztürk (2014) examine the causal relationship between oil price and industrial production index for G7 countries and provide evidence that the oil price shocks might affect the industrial production of the net energy importing countries. Sakashita and Yoshizaki (2016) examine the impact of oil price shock on industrial production in five emerging countries, showing that oil price shocks on the industrial production index in emerging nations react to where the changes come from. Similarly, Scholtens and Yurtsever (2012), considering European countries, examine the effects of oil price shocks on 38 industrial production indices. They reveal that the impact of oil price shocks radically differs along with the various industries. Awartani et al. (2020) find robust results that growth in MENA nations is connected with oil prices because it benefits from higher oil prices, and it gets hurt by a fall in the oil market.

In addition to this issue, a number of scholars have recently expressed an interest in the quality of official Chinese data. Cross and Nguyen (2017) use a class of time-varying Bayesian vector autoregressive models to capture the nexus between China's economic growth and the global oil market. Tang et al. (2010) employ a structural vector autoregressive model to answer how oil price shocks influence China's economy. They argue that an oil price rise negatively impacts economic activity in China. He (2020) finds a significant non-linear Granger causality association run from oil price to Chinese investor sentiment. Chen et al. (2020) report that an increase in oil prices caused by oil supply shocks has negative influences on economic activity in China. Specifically, according to Chen et al. (2020), the effects of oil price shocks on output upstream to downstream in the industrial oil chain are time-varying, and the dynamic affects shift in China's economy at varied lag lengths.

As for the methodologies to explore the interrelatedness between crude oil prices and economic activity, most previous researchers use the conventional linear Granger test, VAR, VECM model (Jo, 2014; Yıldırım & Öztürk, 2014; Cobo-Reyes & Perez Quiros, 2005; Eryiğit, 2012; Mehrara & Sarem, 2009), VAR-GARCH (Elder, 2018), SVAR (Herrera et al. 2011; Chen et al. 2020), and dynamic conditional correlation (He, 2020) are also applied to measure the nexus between the two variables.

Recently, several scholars used a wavelet technique to assess the co-movement between the global oil market and industrial output. For example, Dong et al. (2019) investigate the dynamic connectedness between global economic activity and crude oil prices using the wavelet approach. They uncover that the correlation between crude oil prices and global economic activity is significant at high frequencies, and it depends on the time scale. In a similar fashion, Aloui et al. (2018) suggest that the dynamic relationship between the oil market and industrial output in Saudi Arabia evolves through time and frequency. The results also show strong but non-homogeneous correlations between the two variables. Benhmad (2013) unveils that crude oil prices are leading the economic activity by three quarters and lagging the US business cycle. Given the conclusion in the existing literature and the significant intercorrelation between oil prices and economic activity, understanding their inner nexus seems crucial. In this paper, we examine the time-varying spillover effects between crude oil, oil future prices, and economic activity in China from a multiscale perspective, making up for the shortcomings of the above methods. Besides, the VAR-GARCH-BEKK model is used to successfully capture the price and volatility spillover effects between oil markets and economic activity at various time horizons.

METHODOLOGY AND DATA

The Continuous Wavelet Transform

The wavelet transform $W_x(s)$ is required by estimating a definite wavelet $\psi(.)$ against the time series $x(t) \in L^2(R)$ for both frequency and time.

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

The significant property of the continuous wavelet transform is the capacity to decompose and then recreate a time series $x(t) \in L^2(R)$. The asterisk (*) represents the complex conjugate in which the wavelet can detect higher or lower elements of the $x(t)$.

Discrete Wavelet Transform

The time sequence $y(t)$ can be decomposed into different scales:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (2)$$

where the mother wavelet function is ψ and father wavelet function is ϕ. The smooth (low frequency) $s_J(t)$ is parts of a signal and detail (high frequency) $d_J(t)$ is elements. We can rewrite the $y(t)$ as follows:

$$y(t) = S_j(t) + D_j(t) + D_{J-1}(t) + \cdots + D_1(t) \quad (3)$$

where the smooth signal is the highest-level approximation $S_j(t)$, and associated with oscillations of lengths 2-4, 4-8, …, $2^j + 2^{j+i}$ is $D_1(t), D_2(t), ..., D_j(t)$, respectively. In this paper, monthly data is used, and we establish J = 4 for multi-resolution level J because previous works demonstrated that a moderate filter was appropriate for financial data (Reboredo et al. 2017; Chen et al. 2019; Hung, 2020).

Wavelet Coherence

To analyzing the relationship between the two variables, we illustrate a bivariate structure termed as wavelet coherence. The cross-wavelet of two sequence $x(t)$ and $y(t)$ can be defined as:

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

where u denotes the position, s is the scale, and * denotes the complex conjugate. The squared wavelet coefficient is defined as:

$$R_n^2(u,s) = \frac{|S\left(s^{-1}W_n^{XY}(u,s))|^2\right)}{S\left(s^{-1}|W_X(u,s)|^2\right)S\left(s^{-1}|W_Y(u,s)|^2\right)} \tag{5}$$

where S is a smoothing mechanism. $R^2(u,s)$ is in the range of squared wavelet coherence coefficient $0 \leq R^2(u,s) \leq 1$, which is analogous to correlation coefficient.

Wavelet Correlation

To provide the background for the casual association between variables, the Rua (2013) wavelet correlation measure is given by:

$$\rho_{XY}(s,\tau) = \frac{\xi\left\{s^{-1}|\Re\left(W_{XY}^m(s,\tau)\right)|\right\}}{\xi\left\{s^{-1}\sqrt{|W_X^m(s,\tau)|^2}\right\}.\xi\left\{s^{-1}\sqrt{|W_Y^m(s,\tau)|^2}\right\}} \tag{6}$$

where $\xi(Q) = \xi_{scale}\left(\xi_{time}(Q)\right)$ with ξ_{scale} as the smoothing operator along scale axis, while ξ_{time} as the smoothing operator along the time axis. As a traditional correlation analysis, $\rho_{XY}(s,\tau)$ is bounded from -1 to +1.

Causality in Continuous Wavelet Transform

The continuous wavelet transforms for the Granger causality developed by Olayeni (2016) is employed, which extends the CWT-based correlation measure by Rua (2013). It can be written as:

$$G_{Y\to X}(s,\tau) = \frac{\xi\left\{s^{-1}|\Re\left(W_{XY}^m(s,\tau)\right)I_{Y\to X}(s,\tau)|\right\}}{\xi\left\{s^{-1}\sqrt{|W_X^m(s,\tau)|^2}\right\}\xi\left\{s^{-1}\sqrt{|W_Y^m(s,\tau)|^2}\right\}} \tag{7}$$

where $W_Y^m(s,\tau)$, $W_X^m(s,\tau)$ and $W_{XY}^m(s,\tau)$ are the wavelet transformations and $I_{Y\to X}(s,\tau)$ as the indicator function which is defined as:

$$I_{Y\to X}(s,\tau) = \begin{cases} 1, & if\ \phi_{XY}(s,\tau) \in (0,\pi/2) \cup (-\pi,-\pi/2) \\ 0, & otherwise \end{cases} \tag{8}$$

Wavelet-based VAR-GARCH-BEKK Model

To specify the price and volatility effects throughout different wavelet scales, we utilize the bivariate VAR-GARCH-BEKK model developed by (Engle and Kroner, 1995) which can explore the direction of spillover effects between two time series. The VAR-GARCH-BEKK model is written as:

$$R_t = \alpha\Gamma R_{t-1} + u_t \tag{9}$$

$$u_t|\Omega_{t-1} \sim N(0, H_t) \tag{10}$$

where $R_t = \left[R_{1,t}, R_{2,t}\right]$ denotes a vector of IPI and oil market prices, the vector of the constant is A which presents 2×2 vector. $u_t = \left[\varepsilon_{1,t}, \varepsilon_{2,t}\right]$ is bivariate and a conditional normal distribution, which is the residual vector,. Ω_{t-1} is the market information set available at time $t-1$. H_t shows the conditional covariance matrix and is a function of lagged cross products of errors. The lag selection is reported in Appendix A. The covariance matrix $H_{ij,t} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}$ is for bivariate GARCH model, its BEKK model as follows:

$$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \mathbf{A}'\varepsilon\varepsilon'\mathbf{A}_{11} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} \tag{11}$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11,t} & c_{12,t} \\ c_{21,t} & c_{22,t} \end{bmatrix}' \begin{bmatrix} c_{11,t} & c_{12,t} \\ c_{21,t} & c_{22,t} \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}, \varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \tag{12}$$
$$+ \begin{bmatrix} b_{11,t} & b_{12,t} \\ b_{21,t} & b_{22,t} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11,t} & b_{12,t} \\ b_{21,t} & b_{22,t} \end{bmatrix}$$

where C is the 2×2 upper triangular matrices. ARCH effect of volatility is explained by bivariate GARCH model, the element of a_{ij} shows the effect of market i volatility on market j, while GARCH effect of volatility is demonstrated by bivariate GARCH model, the component of b_{ij} indicates the existence of volatility spillover between market i and market j.

Data

This study aims to identify the influence of the global oil market on the industrial output in China. The data sets we selected for this research consist of monthly data of oil price (OIL), oil future price (OILF), and industrial production index (IPI) measures for economic activity in the case of China (Raza et al., 2018). We collect the monthly data from January 1999 to September 2019 from the Bloomberg database and yielding 250 observations. Due to the data availability of IPI, all variables are from January 1999. Additionally, our sample ends in September 2019 due to the commodities complex's recent high level of volatility on the global financial markets (Covid-19 outbreak). This uncertainty may cause sample heterogeneity in our analysis because of the drastic changes in oil production that OPEC and its allies have made (discipline in output reduction) (Lee et al., 2021). The data is transformed into natural logarithm form. Table 1 represents the underlying statistical parameters of the said financial time series.

The mean value of OIL, OILF and IPI is positive during the period. The skewness and kurtosis coefficients appear to be a departure from the normal distribution; the Jarque-Bera test officially confirms this. Furthermore, the ADF test suggests that all series are stationary at level (I(0)) at the 1% significance level, and ARCH LM confirms the existence of the ARCH effect in the oil prices, oil future prices, and industrial production index. Therefore, these findings are appropriate for further statistical analysis.

Table 1
Descriptive statistics of monthly returns of the IPI, OIL and OILF markets

	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Beta	ADF	ARCH-LM
IPI	4.637869	0.058122	0.272899	2.510987	5.571677***	-3.536716***	159.3294***
OIL	3.882371	0.488474	-0.696365	2.510987	20.13558***	-5.628101***	237.6865***
OILF	3.898679	0.462319	-0.556088	2.553510	14.90151***	-5.288664***	241.9262***

Note: *** denotes significance at 1%

EMPIRICAL RESULTS

Multiscale Analysis

The original time series was decomposed using the maximum overlap discrete wavelet transform (MODWT). Oil, oil future prices, and industrial production data are decomposed into a series of four time scales (D_1, D_2, D_3, and D_4) that display detailed information about the raw data, as well as an S4 trend element. The wavelet scale is shown in Table 2 for further information.

Table 2
Corresponding relationship between time and scale

Detail	Wavelet Scale	Frequency
D_1	1	2-4 months
D_2	4	4-8 months
D_3	8	8-16 months
D_4	16	16-32 months
S_4	>16	Above 32 months

Figure 1 shows the related variable fluctuations based on the CWT. The yellow island at the bottom (top) of the CWT illustrates significant change at low (high) frequencies while the yellow area on the left-hand side (right-hand side) depicts substantial variation at the beginning (end) of the sample period, and regions in blue show weak fluctuation or low intensity between indicators. In other words, oil markets and economic activity experience significant volatility at the 5% significant level.

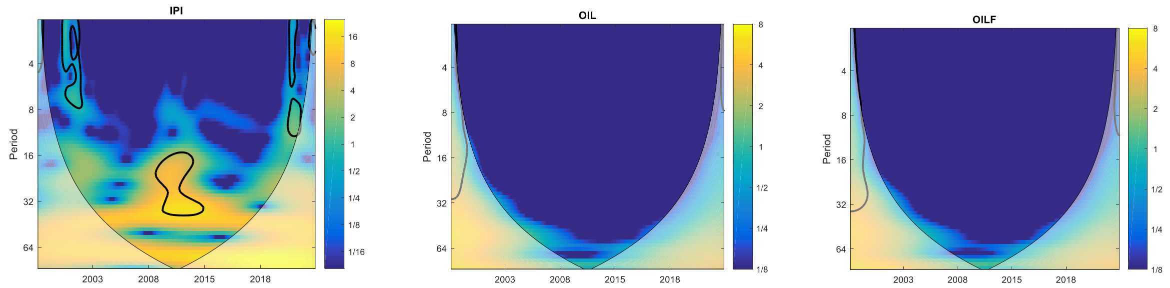

Figure 1. Continuous wavelet power spectra of OIL, OILF and IPI

The cross-wavelet transformation (XWT) between two-time series in a pairwise manner is summarized in Figure 2. The XWT reflects the local covariance between OIL, OILF, and IPI series at different scales and periods. It is clear that the covariance for all such pairs has dramatically increased with scales. The vertical axis demonstrates the interdependence between the two variables under analysis impacted by medium to long-term variations than short-term innovations. In this figure, we can also conclude concerning the phase (the arrows). Information in connection with phase difference infers that the nexus among concerned variables was not homogeneous across scales because arrows point up and right, down and up constantly.

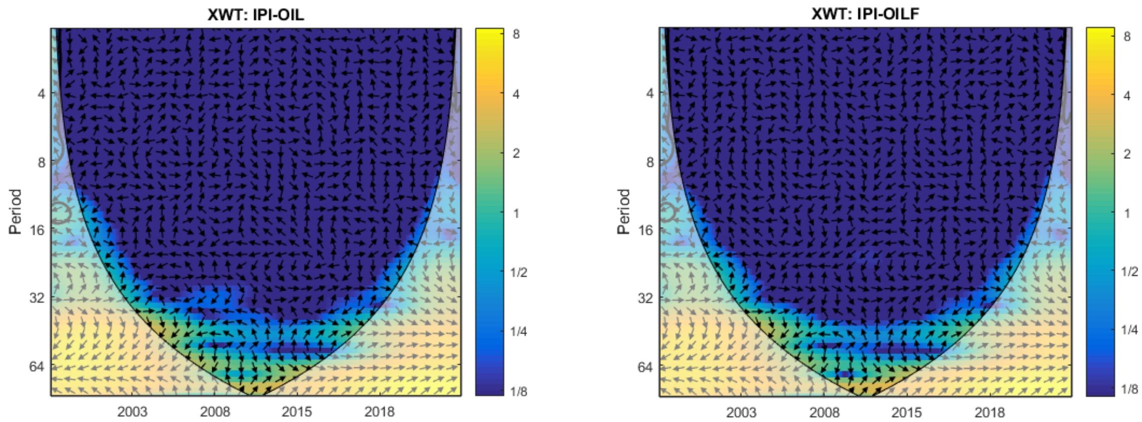

Figure 2. Cross-wavelet transforms for OIL, OILF and IPI

Figure 3 allows us to look at the estimated wavelet coherence and phase difference between IPI and oil prices in China. The yellow island at the bottom (top) of the wavelet coherence indicates strong interplay at low (high) frequencies, whereas the yellow region on the left (right) side indicates a significant correlation at the start (end) of the sample period. The color codes represent the degree of correlation between the variables under examination. The yellow regions present that two series exhibit strong relationship, while blue color areas present that two series are weakly connected. Furthermore, the wavelet coherence effectively performs zones in different time and scales where each pair of series is significantly dependent on the other, or vice versa.

Wavelet coherence plots suggest that OIL and OILF prices were lagging industrial production index in China in very special episodes in history, while the highest and spreader effect for almost frequencies was especially changed during the global financial crisis 2007-2008. In 2008-2013, the bidirectional causal relationship was found between IPI and OIL as well as IPI and OILF in China.

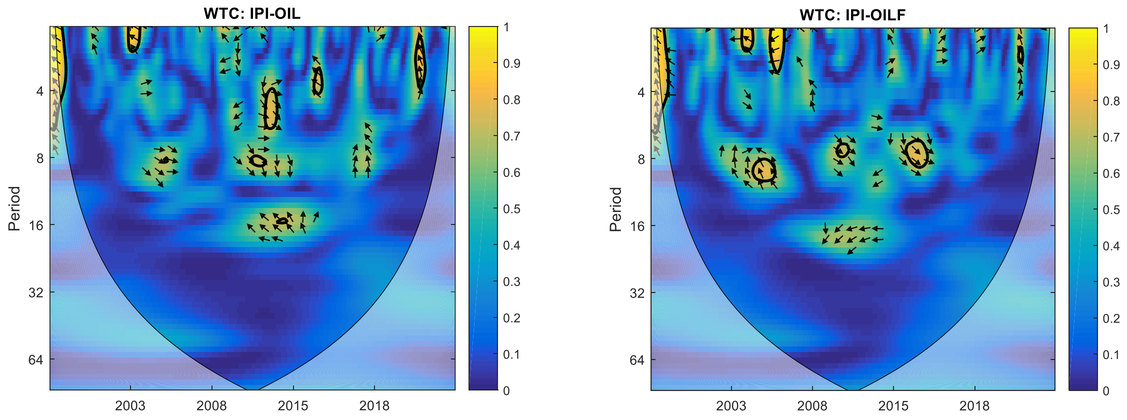

Figure 3. Wavelet coherence of OIL, OILF and IPI

Directions of arrows were not identical throughout the plots for respective time series pairs. The existence of in-phase and out-phase interactions suggesting the positive and negative relationship is thus clearly visible. Overall, based on the wavelet coherence analysis, the outcome unveils that oil and oil future prices have a weak impact on IPI in the short term and medium run, while the strong bidirectional association between OIL and IPI in the long run. These results support Raza et al. (2018), who confirm that there is a bidirectional connection between crude oil prices and industrial production index in the United States.

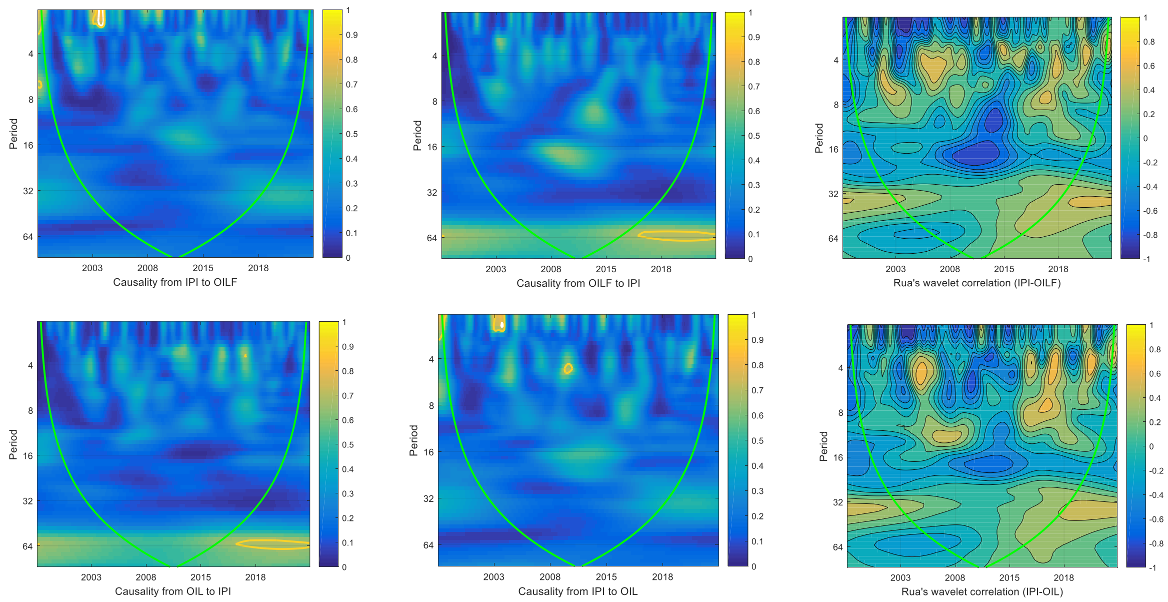

Figure 4. Wavelet based causality and wavelet-based correlations Rua (2013) between OIL and IPI.

Figure 4 describes the time and frequency causality and correlation between oil prices and economic activity in China. The plots at the bottom refer to the Rua correlations between the two variables. We can observe that oil prices have a stronger relationship with economic activity compared to oil future market. High positive correlations occur within the cone of influence in the period of 2008-2014 in the low and medium term. Other these small patches, the relationship between the two variables is negative in the long run. As shown in Figure 4, it is evident that at the high frequency the co-movement between oil prices and economic activity experienced increasing trend, especially after the global financial crisis 2008. Additionally, it reached its peak in 2010. Specifically, in the low frequency indicates that the co-movement attained its peak in 2013. Therefore, our results match the observed behavior between oil prices and economic activity. This outcome not only indicates the nature of the factors responsible for the causal association but also the historical growth of such a connection.

At the next stage, time-frequency price and volatility spillover effects between economic activity and oil markets are conducted. More specifically, we use the VAR-GARCH-BEKK model based on each wavelet scale.

Spillover Effects

Price spillover

First, we take into account the mean spillovers between oil markets and IPI in China at each wavelet scale. As shown in Tables 3-6, we can observe that OIL, OILF and IPI are all impacted by their own lagged values throughout different time scales because of the significant coefficients of μ_{11} and μ_{22}. These coefficients are both negative and positive at different scales, which means that the connectedness direction between OIL, OILF and IPI changes in different time and frequencies. Therefore, it is crucial to differentiate a negative or positive relatedness, which allows market participants to modify strategies promptly to keep away from market risk, these findings tally with the previous studies (Taspinara, 2015; Ahmed et al. 2017; Hung, 2021). Second, OIL, OILF prices and IPI are not only influenced by their own lagged values but are also impacted by the IPI/OIL markets. From the price spillover perspective, the price spillovers between OIL, OILF and IPI in China are unidirectional linkages or there is no relationship. We summarize the outcomes of the price spillover effects between OIL, OILF and IPI in Table 7.

Volatility spillover

We now consider volatility spillovers between three indices during the four wavelet scales. Tables 3-6 reports the results of the conditional variance and residual, gained from the estimation of the VAR-GARCH-BEKK model. The diagonal components measure the own ARCH effects in matrix A, while the diagonal components of matrix B measure the own GARCH effects. Throughout the visual inspection of these tables, the coefficients of a_{11}, a_{22} are significant at all the wavelet scales, which reveal the existence of the ARCH effect. Put another way, the higher levels of conditional variance of IPI prices and oil markets are influenced by their own past innovations. Similarly, b_{11}, b_{22} coefficients are also statistically significant for all cases, which suggests the persistence of GARCH effects. This implies that their own past conditional variance considerably impacts the current conditional variance of oil, oil future prices and IPI.

Table 3
Estimation results of the VAR- BEKK-GARCH model for scale D1

	IPI-OIL	IPI-OILF
Mean Equation		
μ_{11}	-0.448898498*** (0.048669130)	-0.366308352 *** (0.033664458)
μ_{12}	0.044861589*** (0.006467346)	0.069932487 *** (0.005564781)
μ_{I}	-0.000120311 (0.000092924)	-0.000174823 * (0.000091884)
μ_{21}	-0.041066265*** (0.017646601)	0.021848816 (0.020949666)

μ_{22}	-0.353720564*** (0.062971666)	-0.228104770*** (0.063907866)
μ_O	-0.000111331 (0.000085768)	-0.000154110 (0.000140638)
Variance equation		
c_{11}	0.000687563*** (0.000172201)	0.000952149 *** (0.000170638)
c_{21}	-0.000552908** (0.000327866)	-0.000667217 (0.000508602)
c_{22}	0.001070115 *** (0.000263483)	0.001827666*** (0.000256031)
a_{11}	1.093498793 *** (0.112605036)	1.286409337 *** (0.095096702)
a_{12}	-0.050993744 (0.044920006)	0.002800196 (0.046434258)
a_{21}	-0.047471040** (0.021147082)	0.031870450* (0.018884296)
a_{22}	1.197769715*** (0.106191515)	1.078166254*** (0.093926143)
b_{11}	0.707040109*** (0.047498339)	-0.59015193*** (0.041449859)
b_{12}	0.049627678* (0.021137319)	0.094387850 ** (0.046338491)
b_{21}	0.010816181 (0.009350726)	-0.019718000 (0.015564895)
b_{22}	0.525050755*** (0.041663279)	0.372994630 *** (0.102516774)
ARCH-LM	40.00 [0.68345]	47.17[0.38394]

Note: *,**,*** indicate significance levels at 10%, 5% and 1% respectively. Standard errors are represented in parentheses. P-values are given in brackets.

Table 4
Estimation results of the VAR- BEKK-GARCH model for scale D2

Mean Equation	IPI-OIL	IPI-OILF
μ_{11}	0.518566982*** (0.046943905)	0.518185246*** (0.043634619)
μ_{12}	0.040244849*** (0.002682514)	0.044882362*** (0.002637266)
μ_I	0.000124677 (0.000182765)	0.000219229 (0.000188489)
μ_{21}	0.035416855 *** (0.013276275)	-0.043522231 (0.019157357)
μ_{22}	0.607119028 *** (0.039719295)	0.680602059*** (0.049920858)
μ_o	0.000024453 (0.000120293)	0.000045894 (0.000118764)
Variance equation		
c_{11}	0.001358977*** (0.000189098)	0.001521860*** (0.000259334)
c_{21}	-0.000134689 (0.000139934)	0.000061347 (0.000179649)
c_{22}	-0.000780290*** (0.000144889)	-0.000775699*** (0.000137815)
a_{11}	1.015874409 *** (0.077850760)	1.088362430*** (0.084398505)
a_{12}	-0.037191265 (0.030147920)	0.024391244 (0.042603285)

a_{21}	0.029704505*** (0.005975333)	0.029868925*** (0.010088568)
a_{22}	0.875080923*** (0.061205892)	0.884811615*** (0.064172600)
b_{11}	0.608378699*** (0.037156110)	0.555260735*** (0.045512865)
b_{12}	0.021934752 (0.013627481)	-0.024154996 (0.026409400)
b_{21}	0.015302492*** (0.003951402)	0.018899171*** (0.006686389)
b_{22}	0.687303166*** (0.026288098)	0.695585285*** (0.025109564)
ARCH-LM	15.24[0.9245]	15.133 [0.9121]

Note: *,**,*** indicate significance levels at 10%, 5% and 1% respectively. Standard errors are represented in parentheses. P-values are given in brackets.

Table 5

Estimation results of the VAR- BEKK-GARCH model for scale D_3

	IPI-OIL	IPI-OILF
Mean Equation		
μ_{11}	0.847053561*** (0.024875486)	0.847053561*** (0.024875486)
μ_{12}	-0.009051186*** (0.002039049)	-0.009051186 (0.002039049)
μ_I	0.000215859 (0.000221063)	0.000215859*** (0.000221063)
μ_{21}	0.001743164 (0.013634848)	0.001743164 (0.013634848)
μ_{22}	0.873749242*** (0.039827772)	0.873749242*** (0.039827772)
μ_o	-0.000015880 (0.000106483)	-0.000015880 (0.000106483)
Variance equation		
c_{11}	0.000610277*** (0.000161633)	0.000610277*** (0.000161633)
c_{21}	0.000241089*** (0.00009119)	0.000241089*** (0.000091194)
c_{22}	0.000000009 (0.000404680)	0.000000009 (0.000404680)
a_{11}	0.913314228*** (0.063852955)	0.913314228*** (0.063852955)
a_{12}	-0.004885134 (0.016793970)	-0.004885134 (0.016793970)
a_{21}	0.005863565** (0.003089380)	0.005863565* (0.003089380)
a_{22}	0.909536568*** (0.056405613)	0.909536568*** (0.056405613)
b_{11}	-0.591482393*** (0.037433914)	-0.591482393*** (0.037433914)
b_{12}	-0.034093236 (0.066862200)	-0.034093236 (0.066862200)
b_{21}	-0.028454172*** (0.003516070)	-0.028454172*** (0.003516070)
b_{22}	0.602471602*** (0.029431372)	0.602471602*** (0.029431372)
ARCH-LM	21.73[0.4570]	21.68 [0.4101]

Note: *,**,*** indicate significance levels at 10%, 5% and 1% respectively. Standard errors are represented in parentheses. P-values are given in brackets.

Table 6: Estimation results of the VAR- BEKK-GARCH model for scale D4

	IPI-OIL	IPI-OILF
Mean Equation		
μ_{11}	0.972848940*** (0.015752435)	1.007637934*** (0.015285095)
μ_{12}	-0.005731106*** (0.001237165)	-0.00706423*** (0.001113413)
μ_I	-0.000092044 (0.000282653)	-0.000095793 (0.000327141)
μ_{21}	-0.002337637*** (0.006983315)	0.014278553*** (0.003212550)
μ_{22}	1.052353945*** (0.006983315)	0.987527495*** (0.004301925)
μ_o	0.000030939 (0.000076017)	-0.000276765*** (0.000114915)
Variance equation		
c_{11}	0.000718763*** (0.000100381)	0.000471126*** (0.000094028)
c_{21}	-0.000169842*** (0.000045866)	-0.000263185*** (0.000052419)
c_{22}	-0.000108341 *** (0.000038088)	0.000000142 (0.000127027)
a_{11}	1.105972841 *** (0.062911986)	0.001356544*** (0.057301350)
a_{12}	0.003272195 (0.004801787)	0.001356544 (0.005770495)
a_{21}	-0.004625545 (0.002920415)	-0.002671395 (0.003428786)
a_{22}	1.245060705 *** (0.068871419)	0.995256212*** (0.054345582)
b_{11}	0.423859872 *** (0.032304624)	0.455865669*** (0.035997301)
b_{12}	-0.006516530 * (0.002786461)	-0.035412834*** (0.003139069)
b_{21}	0.000889637 (0.002540779)	0.004778980 (0.003139069)
b_{22}	0.450572928*** (0.026421298)	-0.329803914*** (0.037550622)
ARCH-LM	77.77 [0.1405]	78.77 [0.1370]

Note: *,**,*** indicate significance levels at 10%, 5% and 1% respectively. Standard errors are represented in parentheses. P-values are given in brackets.

Table 7
Mean and volatility spillovers between industrial production index and oil prices

	IPI-OILF	IPI-OIL
Mean spillover		
D_1	$OILF \rightarrow IPI$	$OIL \rightarrow IPI$
D_2	$IPI \rightarrow OILF$	$IPI \rightarrow OIL$
D_3	$OILF \rightarrow IPI$	$OIL \rightarrow IPI$
D_4	NO	NO
Volatility spillover		
D_1	$IPI \rightarrow OILF$	$IPI \rightarrow OIL$
D_2	$OIL \rightarrow IPI$	$OILF \rightarrow IPI$
D_3	$OIL \rightarrow IPI$	$OILF \rightarrow IPI$
D_4	$IPI \rightarrow OIL$	$IPI \rightarrow OIL$

Note: The symbols $\rightarrow$ represents the direction of shock and volatility spillovers from OIL/OILF to IPI and vice versa. "NO" means there are no shock and volatility spillovers between the two series.

Let us take into consideration the off-diagonal components of matrices A and B, these parameters show the volatility spillovers across various time series. The outcomes of the significant coefficients of a_{12}, a_{21}, b_{12}, b_{21} illustrate that the interdependence between OIL, OILF and IPI in China changes across various time scales. It is clear that there exist unidirectional and bidirectional volatility spillovers or non-persistent volatility spillovers between oil markets and the industrial production index in China. For example, the parameter estimates of a_{12} are not statistically significant for the cases of IPI-OIL at scale D_1, IPI-OILF at scale D_4, which means that the past shocks of the IPI in China do not affect the present volatility of oil and oil future prices. In the opposite direction, a_{21} coefficients are statistically significant at scale D_2, D_3 and D_4. This implies that the past shocks of the oil markets have a significant influence on the conditional volatility of the industrial production index in China. Regarding the GARCH effects, b_{12} coefficients are statistically significant at scale D_1 and D_4, which shows the unidirectional volatility spillovers from IPI to OIL, while coefficients of b_{21} are significant at scale D_2 and D_3. This finding demonstrates that there is a bidirectional volatility spillover between IPI and oil prices at wavelet scale D_2, and unidirectional volatility spillovers from oil, oil future prices to the industrial production index in China. Table 7 reports all the volatility spillover effects between IPI and oil prices at different wavelet time scales.

The findings in Tables 3-6 vividly depict the persistence, strength, and direction of spillover effects between the variables under investigation. We use the multivariate ARCH-LM test on the residuals of each model to determine whether the ARCH effect is still present in the model (Hung, 2019). The results show that there is no problem with the ARCH effect, implying that the VAR-GARCH-BEKK model is appropriate. As a result, modeling the VAR-GARCH-BEKK model accurately captures the mean and volatility spillovers between oil markets and Chinese economic activity.

In the model computation, hypothesis H1 was found to be statistically significant, which means that oil price shocks have a negative impact on economic activity in China in the short and medium runs.

Further Analysis

Several scholars have examined the asymmetric interaction between economic indicators using asymmetric causality tests of Hatemi (2012). To further estimate the non-linear nexus between economic activity and oil prices in China, we utilize the causality tests developed by Hatemi (2012), which is a robust model for investigating the causal relationship between two-time series. The model has been used in some recent works (Baz et al., 2020; Tugcu et al., 2012; Shahbaz et al., 2017). The results are documented in Table 8. With regard to asymmetric causality, Table 8 shows the causal links running from IPI to OIL and OILF at D_0, D_1, D_3 and D_4 levels. In addition, there exist causal linkages running from OIL to IPI at D_2. However, Table 8 also reports that there are no causal linkages between OIL, OILF, and IPI in the short, medium, and long run. It is true in the case of the D_0 level. In general, our findings reinforce the existing literature in highlighting that the selected variables under consideration connect in a nonlinear manner. We also show strong evidence to support the hypotheses that changes in the causing variables are significant for detecting the true causality associations hidden behind the variables' fundamental causality dynamics.

Table 8
Results for asymmetric causality

Causality	Wald test	CV at 1%	CV at 5%	CV at 10%	Causal
D_0					
$IPI^{+} \rightarrow OIL^{+}$	2.161	7.275	5.241	1.145	Yes
$IPI^{-} \rightarrow OIL^{-}$	0.566	12.540	5.697	2.374	No
$OIL^{+} \rightarrow IPI^{+}$	2.005	6.244	5.006	2.571	No
$OIL^{-} \rightarrow IPI^{-}$	1.410	38.215	17.364	14.025	No
$IPI^{+} \rightarrow OILF^{+}$	8.056	13.214	8.870	8.557	No
$IPI^{-} \rightarrow OILF^{-}$	2.780	19.214	15.299	11.674	No
$OILF^{+} \rightarrow IPI^{-}$	4.528	11.021	6.354	5.606	No
$OILF^{+} \rightarrow IPI^{+}$	3.501	9.677	4.657	3.914	No
D_1					
$IPI^{+} \rightarrow OIL^{+}$	0.484	15.94	2.780	1.907	No
$IPI^{-} \rightarrow OIL^{-}$	2.003	69.970	8.561	1.078	Yes
$OIL^{+} \rightarrow IPI^{+}$	2.007	10.547	8.664	8.024	No
$OIL^{-} \rightarrow IPI^{-}$	6.180	25.360	18.114	14.072	No
$IPI^{+} \rightarrow OILF^{+}$	0.506	5.210	2.770	2.013	No
$IPI^{-} \rightarrow OILF^{-}$	5.255	10.306	4.528	2.588	Yes
$OILF^{+} \rightarrow IPI^{-}$	0.483	5.046	2.251	1.072	No
$OILF^{+} \rightarrow IPI^{+}$	1.716	8.883	5.504	4.054	No
D_2					
$IPI^{+} \rightarrow OIL^{+}$	0.776	14.507	8.985	8.261	No
$IPI^{-} \rightarrow OIL^{-}$	1.257	9.006	5.217	3.674	No
$OIL^{+} \rightarrow IPI^{+}$	0.815	9.756	7.521	3.458	No
$OIL^{-} \rightarrow IPI^{-}$	2.417	6.331	3.214	2.017	Yes
$IPI^{+} \rightarrow OILF^{+}$	0.656	2.901	1.833	1.021	No
$IPI^{-} \rightarrow OILF^{-}$	1.025	8.664	5.204	3.331	No
$OILF^{+} \rightarrow IPI^{-}$	0.948	2.775	2.024	1.541	No
$OILF^{+} \rightarrow IPI^{+}$	0.05	5.344	2.078	1.704	No
D_3					
$IPI^{+} \rightarrow OIL^{+}$	6.777	133.047	26.451	22.0178	No
$IPI^{-} \rightarrow OIL^{-}$	5.215	128.601	22.394	14.007	No
$OIL^{+} \rightarrow IPI^{+}$	0.114	118.214	35.467	30.014	No
$OIL^{-} \rightarrow IPI^{-}$	0.225	58.039	41.101	16.394	No
$IPI^{+} \rightarrow OILF^{+}$	9.950	14.033	2.610	2.034	Yes
$IPI^{-} \rightarrow OILF^{-}$	2.660	17.228	8.271	3.220	No
$OILF^{+} \rightarrow IPI^{-}$	0.726	11.240	2.550	1.757	No
$OILF^{+} \rightarrow IPI^{+}$	0.029	6.503	2.666	1.920	No
D_4					
$IPI^{+} \rightarrow OIL^{+}$	5.687	7.007	2.877	2.630	Yes
$IPI^{-} \rightarrow OIL^{-}$	2.141	3.339	1.927	1.115	Yes
$OIL^{+} \rightarrow IPI^{+}$	5.579	8.597	3.667	2.048	Yes
$OIL^{-} \rightarrow IPI^{-}$	2.201	15.247	9.372	6.258	No
$IPI^{+} \rightarrow OILF^{+}$	6.034	6.701	4.222	4.015	Yes

$IPI^- \rightarrow OILF^-$	3.547	33.609	12.417	5.630	No
$OILF^+ \rightarrow IPI^-$	4.548	22.405	8.901	6.991	No
$OILF^+ \rightarrow IPI^+$	0.077	3.871	2.091	1.673	No

Note: D_0 represents data without wavelet decomposition. CV presents the critical value. *,**, and *** presents 10%, 5% and 1%, respectively. The superscripts "+" and "-" denote positive and negative shocks, respectively.

DISCUSSION

The price of crude oil has recently risen globally. China is one of the emerging countries experiencing rapid economic growth. Oil price increases pose a serious problem for oil-importing countries. This paper is primarily concerned with oil prices and economic activity. We discover evidence of significant relationships between changes in oil prices and economic growth. Our findings back up the findings of Cross and Nguyen (2017) and Tang et al. (2010). In addition, there is evidence of volatility spillovers from changes in oil prices to economic growth, which supports the studies of He (2020) and Chen et al. (2020) that the effect of oil prices on economic activity varies over time. This information transmission between oil price and economic growth implies that a sudden increase in oil price increases the risk of reduced economic activity. Because China produces a small amount of crude oil, accurate information on oil prices is critical for economic activity.

Furthermore, the influences of global oil market shocks on economic activity in China at different time and frequencies are statistically significant, which implies that oil demand shocks are the key determinant that impacts industries' output. The valuable information provided by these outcomes supports several divergences in the short, medium, and long-term nexus between oil prices and economic activity in China in terms of the leadership, causality, price, and volatility effects, which provides vital implications for institutional investors and policymakers in this country. Our findings are consistent with Cross and Nguyen (2017), Aloui et al. (2018), Benhmad (2013), and Chen, Zhu and Zhong (2021).

CONCLUSION, IMPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

For the first time, this article integrates the wavelet transform approach and multivariate GARCH model to analyze the co-movements and volatility spillover effects between oil, oil future prices, and the industrial production index in China at different time horizons throughout 1999-2019. By doing so, we model and propose a multiscale analysis framework. We first capture the causal association between global oil markets and industrial output in China utilizing the wavelet transform frameworks. This novel method enables the decomposition of time-series at various time and frequencies based on short-run, medium-run, and long-run. Unlike the present literature on the oil-output relationship, which focuses on a higher frequency, such as yearly and quarterly data, monthly data is employed. The wavelet-Granger causality test developed by Olayeni (2016) is used to quantify the strength and direction of causal links over time and across multiple frequencies at the same time. We further implement an analysis of price and volatility spillover effects between the variables by incorporating the VAR-GARCH-BEKK model into the MODWT method to determine the direction of risk transmission between oil markets and the industrial production index in China at each wavelet scale.

The empirical findings of the cointegration analyses indicate a significant long-run interconnectedness between oil, oil future prices, and Chinese economic activity. The empirical results of the wavelet transform approach confirm that oil and oil future prices have a significant impact on economic growth in the short-run and medium-run. More importantly, in the long run, there is a neutral effect between oil, oil future prices, and economic activity. Further, we find that the spillover effects between oil markets and economic activity in China are significantly time-varying and spread across various wavelet scales. The price and volatility spillover, unidirectional, and no relationships are found between oil markets and the industrial production index. Also, the volatility spillover effects mainly take place in the medium and long run. China lacks sufficient fossil fuel resources, and its economy is heavily reliant on crude oil imports from oil-producing countries. The country's economic activity is reliant on imported crude oil, making it sensitive to oil price fluctuations (Taspinara, 2015). Given the link between oil prices and economic activity, it might be claimed that hedging oil price uncertainty is a critical determinant for China's long-term industrial output sustainability and stability.

The spillover effect heterogeneity between oil markets and economic activity in China has important implications for the government, policymakers, and other market participants. In the short and medium-term, volatility transmissions were found between economic growth and oil prices in China. Hence, global investors or policymakers could take the variation of crude oil markets or IPI information into account. In the long run, there are bidirectional volatility spillovers between oil prices and economic activity in China, which should be considered by the Chinese government and policymakers to make the right decision. More precisely, because volatile oil prices appear to be having a negative impact on China's economic growth, considering strategic oil reserve utilization to mitigate the effect may be sufficient. This means selling it when prices are high and vice versa.

Since changes in oil prices have various effects on China’s economic activity, the authorities should take effective solutions based on the source of the oil price shocks. Firstly, policies aimed at stabilizing inflation should take into account variations in the international economy, which means that the government needs to change its output model and increase demand for consumption. Secondly, China, as the world's second-largest oil consumer and importer, should be aware of its significant reliance on oil imports and the resulting imported inflation. The Chinese government should limit the use of fossil fuels, reduce energy intensity, and increase energy efficiency to successfully combat inflation. Thirdly, in order to mitigate oil-specific demand innovations, the government should enhance market-oriented energy pricing and, as soon as possible, establish an energy financial system and an open crude oil futures market. Furthermore, the price-control policy in China has to be changed. As a result of the increased inflationary pressure caused by increasing oil prices, the market mechanism must be improved, as well as the efficiency and fairness of the market price adjustment process, to decrease human-induced bias. More so, the Chinese authorities must consider industrial disparities in the effects of oil price shocks on economic growth when establishing anti-inflationary measures, and adopt differentiated policies based on the fact that each industry responds differently to oil price shocks.

In line with the findings, we propose motivating future research directions to better understand the influence of oil prices on microeconomic indicators, particularly in emerging economies. More macroeconomic variables may improve the results and contribute to the relevant literature. Finally, we propose that the work should be expanded by employing an advanced econometric framework such as the time-varying Granger causality developed by Shi et al. (2020) to explain these relationships fully.

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APPENDIX A

The optimal lag order analysis

Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	887.7400	NA	1.30e-07	-7.342241	-7.298861	-7.324764
1	2295.827	2769.433	1.18e-12	-18.95292*	-18.7794*	-18.88302
2	2305.570	18.91926	1.17e-12	-18.95909	-18.65543	-18.83675
3	2327.477	41.99564	1.05e-12	-19.06620	-18.63241	-18.89143*
4	2336.974	17.96981	1.05e-12*	-19.07032*	-18.50639	-18.84313

Note: * represents lag order selected by the criterion; LR: sequential modified LR test statistic; FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion