Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.18488/journal.aefr.2019.98.913.925
Vol. 9, No. 8, 913-925
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URL: www.aessweb.com

REVISITING OIL PRICES, PRODUCER PRICE INDEX (PPI), AND THE PURCHASING MANAGERS' INDEX (PMI) NEXUS: CHINA AND THE USA

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Article History
Received: 16 May 2019
Revised: 20 June 2019
Accepted: 22 July 2019
Published: 7 August 2019

Keywords
West texas intermediate (WTI)
US Purchasing managers' index (PMI)
Chinese purchasing managers' index (PMI)
US Producer price index (PPI)
Chinese producer price index (PPI)
Wavelet theory

JEL Classification:
A10; O40; Q43.

ABSTRACT

This study examines the lead–lag effect between the Chinese and US purchasing managers' index (PMI), and the West Texas Intermediate (WTI) crude oil prices for the period from January 2007 to April 2017 by adopting the wavelet theory model. The results show that oil prices were affected by the Chinese PMI in the long term after 2013, when China became the largest crude oil importer worldwide, bur supplies were greater than demand. In contrast, while the US PMI affected oil prices between 2008 and 2012, its dependence on foreign crude oil supplies declined, and thus its imports, afterwards. These results reveal crucial policy implications for both China and the United States. It also shows a structural change in oil prices and its role in the market between China and the United States.

Contribution/Originality: This study contributes to the existing literature by examining the lead–lag effect between the Chinese and US purchasing managers' index (PMI), and the West Texas Intermediate (WTI) crude oil prices for the period from January 2007 to April 2017.

1. INTRODUCTION

In recent years, there has been a significant transformation in oil supply and demand. In the United States, shale oil has undergone numerous innovations since 2004: oil production costs dropped significantly and operating efficiency improved, resulting in substantial changes in shale gas production. Entering a stage of commercial development in 2009, US crude oil production escalated, exceeding imports in October 2013 for the first time in nearly two decades. By 2016, the US had become the world's primary oil producer, accounting for 13.2% of total global oil production. However, in December 2015, crude oil exports were banned as the United States changed from its role as *buyer* to that of *seller*. Xiao *et al.* (2014) discovered that US shale gas production led to a revolution in the US manufacturing industry and transformation in the global energy industry its own energy consumption. For example, the cost structure of ethylene products in the petrochemical industry fell far below that of traditional crude oil refining, which benefited both manufacturing and various other industries by attracting increased foreign

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investment and further improving the employment rate. In addition to reduced imports of crude oil, the trade deficit encountered a recession, which prompted the forecast of a gradual narrowing of the manufacturing cost gap between the United States and China.

Simultaneously, China became the world's largest net importer of petroleum in 2013, as the crude oil cost structure was higher than international oil prices. Based on 2013 data, *The Economist* reported that since the international crude oil price declined by 1 USD per barrel, China could save up to 6.7 million USD per day. Therefore, China's oil manufacturing began to decline in 2015 from 4.3 million to 100,000–200,000 barrels per day, and in 2016, its dependency on crude oil imports rose to a remarkable 69%, 4.6% higher than 2015. China is currently far from peak oil consumption, yet, according to the 2014 *Global Energy Outlook* from the International Energy Agency (IEA), its oil consumption will be over three times higher by 2030, requiring a far greater dependence on foreign imports.

This study aims to investigate the nexus between the manufacturing purchasing managers' index (PMI) and international oil prices. Koenig (2002), Yu *et al.* (2011) and Lahiri and Monokroussos (2012) studied the strong relationship between PMI and gross domestic product (GDP), as the former can predict the latter, while Harris (1991) argued that PMI plays a crucial role in predicting industrial production and GDP, and thus a leading economic indicator. Similarly, Zhang and Feng (2012) discovered that PMI was ahead of the GDP trend by 3–12 months, indicating its effectiveness in forecasting economic indicators. It is therefore evident that PMI's prediction power is superior to that of GDP for economic trends and turning points.

This study also uses (PMI) and the West Texas Intermediate (WTI) crude oil price nexus for the main axis analysis of the long and short frequency domains of the Chinese and US PMIs. A lag relationship will be revealed between PMI and international oil prices, showing them to be not mutually exclusive. In addition, the PPI is also used as a robust control variable for an in-depth exploration of its impact on PMI and oil prices in China. Furthermore, this study examines the impact of US manufacturing structural changes after the discovery of shale oil on China, which had the largest trade surplus worldwide with the United States. Hence, the Chinese manufacturing industry and US crude oil prices will be frequently discussed throughout this paper. Finally, an evaluative and in-depth analysis will be presented on the long- and short-term effects of individual dynamics on the PMIs of China and the United States, and the oil prices.

This paper is organized as follows:

- Section 2 reviews the literature.
- Section 3 describes the methodology.
- Section 4 defines the data and sources used for the study.
- Section 5 presents the empirical analysis.
- Section 6 offers the conclusions.

2. LITERATURE REVIEW

Research has indicated a positive correlation between global oil consumption and economic growth (Kraft and Kraft, 1978): global economic growth drives demand for crude oil, which, in turn, affects international crude oil prices, and can also cause supply shortages (Kilian, 2009). However, exceptionally high oil prices will affect the demand for crude oil, because the cost shift will immediately influence commodity prices as well as inflation. The resulting increase in the unemployment rate, though, will both stimulate overall economic growth and initiate a decline in the price of financial assets (Shimon and Raphael, 2006).

In view of the relationship between international crude oil demand and price, most theoretical studies contend that any change in price can lead to increased price rates and exert inflationary pressure on China's internal economy. In other words, as international oil prices rise, so do domestic oil prices; hence, the prices of oil-related products, and transportation and logistics, increase. However, there are inconsistencies among findings from

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empirical studies and are thus unable to confirm the certainty that changes in oil prices cause inflation. For example, Kilian (2009) discovered that although increased global demand boosted oil prices, which retrospectively increased short-term real GDP in the United States and maintained higher prices over a longer period, specific oil demand continued to reduce real GDP growth and raise oil prices even higher in the United States. Kilian (2009) also affirmed that fluctuations in oil prices caused by any supply shock exerts a weaker impact on US macroeconomic variables, and is of little significance to global output and prices, which are quickly attenuated. Zeng (2008) believed that the impact of volatile oil prices level is delayed in China, being eight months for the Chinese consumer price index (CPI). Wu and Li (2008) argued, in fact, that international oil price fluctuations resulted in increased domestic price levels (CPI) through the producer price index (PPI). In terms of long- and short-term effects from oil price fluctuations, a dissimilarity can be observed in China's CPI, as explained by Ren (2012): there were no substantial effects in the short term, whereas in the long term, an increase instigates a rise in oil prices.

Numerous scholars have explored the impact of dramatic oil price fluctuations on national and global macroeconomies. Bernanke *et al.* (1997) contended that the negative impact of oil price shocks on real economic variables was due mainly to the tightening of monetary policies under inflationary pressure rather than oil price volatility. Therefore, the relationship between oil prices and an unstable US macroeconomy was more likely due to the contrasting responses of monetary policy to inflation. When examining the relationship between crude oil prices and industrial production, Kapetanios and Tzavalis (2004) found that manufacturers' costs increased along with crude oil prices; however, when crude oil prices fell, they observed no change in industrial production. It has also been suggested that oil prices are not related to overall economic variables (Bernanke *et al.*, 1997). Yu *et al.* (2011) investigated the relationship between Chinese PMI and international oil prices, and concluded that there was a long-term causal relationship between PMI and both domestic and international oil prices: fluctuations in Chinese PMI drive domestic and foreign oil prices in the same direction, though with a 5-month lag effect. The analysis revealed that the impact of international oil prices on PMI was, to a certain extent, greater than that of domestic oil prices, leading to a revised lag effect of 10 months. Wu and Li (2008) and Tang and Jiao (2012) agreed that oil prices were positively related to the international economy, but Liu and Jiang (2009) along with Ren (2012), argued that China's overall economy exerted little effect on oil prices.

3. METHODOLOGY

Wavelet analysis will be used in this study to verify the nexus effects among oil prices, PPI, and PMI in both China and the United States. To analyze lead–lag effects (causality) and the interactions between crude oil prices and PMI, numerous scholars have used the vector autoregression (VAR), the vector error correction model (VECM), or Granger causality. For instance, Yu *et al.* (2011) noticed that the dynamic between crude oil prices and the Chinese PMI was largely unstable; hence, he adopted the VECM to estimate the long-term effects and analyze the respective short-term adjustment process.

Most of the aforementioned studies focus on a probable correlation between variables and their lead–lag relationships. The advantage of wavelet analysis, though, is the smooth sampling time, as most time series are nonstationary. Before constructing the research model, unit root verification on the research variables was undertaken to confirm whether the time series were stationary. If the results reveal nonstationary properties, the most common method of elimination is to take the first-order differences; however, this may remove long- and short-term implicit information within the data, especially for nonstationary time series. So altering the model's structure will undermine any interpretation, while the financial time sequence usually indicates a strong nonstationary time series. Wavelet analysis can mitigate these problems, however: primarily, it is able to reveal the components of the nonstationary time and frequency structure and the crucial correlations between variables in the short, medium, and long term. It can also help to illustrate the time sequence x(t) and y(t) for the phase difference between the short-, medium-, and long-term variable lead–lag relationships and the positive and negative

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correlations, which are time–frequency localization properties. Finally, wavelet analysis is the optimal method for this study because it can further help to identify the structural transformation between time series.

There are prior studies that have employed wavelet analysis to analyze and understand the relationship between oil prices and the overall economy. With regard to the US economy, for instance, Aguiar-Conraria and Soares (2011) explored the interaction between crude oil prices and economic activity, while Tiwari *et al.* (2013) examined the relationship between oil prices and the overall economy, establishing a two-way relationship between oil prices and inflation, despite the latter being the leading variable. Tiwari *et al.* (2013) also investigated the dynamic relationship between oil prices and real effective exchange rates in Romania and found that the latter exerted a strong short-term effect on the former. Furthermore, Uddin *et al.* (2017) examined inflation and economic growth in Bangladesh through continuous wavelets and causality, and Aloui *et al.* (2018) discussed the volatility of oil prices and dollar exchange rates, economic growth, and inflation. Nevertheless, few studies have employed wavelet analysis to investigate the relationships between crude oil prices and the US and Chinese PMIs. However, this study aims to address that gap.

For signal analysis, researchers and practitioners employ both wavelet and Fourier transforms to convert and process signals. Wavelet analysis was developed from Fourier analysis, which was first proposed by the French mathematician and physicist, Fourier, in 1822. Here, a stationary time series was divided into a sequence of superpositions of sinusoidal signals of varying frequencies, the amplitude of which could be represented by the Fourier transform coefficients. Therefore, local properties were clearly indicated in the frequency domain, although structural mutations remained unidentifiable. Much later in 1964, Gabor introduced the short-time Fourier transform, whereby each of the numerous small time intervals in the signal were analyzed to determine their frequency spectrums. However, the lack of information on and structural changes in processing of nonstationary time series over a long time could not be fully depicted. A better alternative to the Fourier transform for dealing with nonstationary time series and revealing time–frequency localization was finally discovered in the early 1980s, when Morlet proposed wavelet analysis with time–frequency resolution. This provided the possibility to reveal the hidden time series within a variety of change cycles, better reflect trends across different timescales, and enable a qualitative estimation of future development trends.

Wavelet analysis is predominantly used to analyze long-term data and reconcile any nonlinear signal change cycle. The term “wavelet” means “small wave,” in which “small” refers to its decay and “wave” represents volatility. Waveforms can be either irregular or asymmetric, with an average amplitude of 0 over its entire time interval. The basis of wavelet transform is to obtain a family of functions through translation, to identify the time characteristic, and scale conversion, to determine the frequency characteristic, of the mother function, with which to estimate the original signal. Five different wavelet analysis tools will be presented: continuous wavelet transform, wavelet power spectrum, wavelet correlation, wavelet phase difference, and partial wavelet coherence.

3.1. Continuous Wavelet Transform

This analysis is commonly used to decompose the function of continuous time into wavelets, enabling a time–frequency representation of the signal to be constructed with good time and frequency positioning. First, the original time series is decomposed into a series of base wavelets superimposed with the mother wavelet through position translation and scale stretching. Then, a two-dimensional plane of time–frequency and the original time series is produced, which reveals in the time and frequency domains the details hidden in the original time series. The wavelet transform can be either discrete or continuous, but as the latter is easier to use (Grinsted *et al.*, 2004), it is used more often in the financial and economic fields (Caraiani, 2012; Rua, 2012; Tiwari *et al.*, 2013). In Equation 1, $Z(\tau,s)$ focuses on the principles of the continuous wavelet transform (CWT):

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$$Z_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\, \varphi_{\tau,s}^{*}(\mathrm{t})\mathrm{dt}\; Z_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\, \varphi_{\tau,s}^{*}(\mathrm{t})\mathrm{dt} \qquad (1)$$

x(t): the input signal

s: a scaling parameter that stretches or shortens the frequency

τ: a translation parameter that adjusts the time shift.

$\varphi_{\tau,s}^{*}(\mathrm{t})\,\varphi_{\tau,s}^{*}(\mathrm{t})$: the complex conjugate, which is a wavelet base function.

Different wavelet base functions are generated from the same base wavelet ψ(t), derived from the scaling and translation parameters. For instance, in Equation 1, both s and τ are constant varying parameters for signal x(t). Taking details from a high frequency section whereby the smaller the scale factor, the narrower the waveform, while a large scale factor meant a wide waveform, being a measure of the smoothness of the signal.

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \qquad (2)$$

s : the scale parameter that controls how the mother wavelet is stretched

τ : the location parameter that determines where the wavelet is centered.

Therefore, $\psi_{s,\tau}(t)$ in Equation 2 can be defined as the continuous mother wavelet function, and Z(τ,s) the CWT function. As the mother wavelet function—$\psi_{s,\tau}(t)$—of the wavelet transform, it is a special waveform. First, the mean of the mother wavelet function must be 0—∫ + ∞ ψ (t) dt = 0—meaning that it has an alternating positive–negative volatility and is only localized to non-zero. Second, the square integral of the mother wavelet function must be equal to 1—$\int_{-\infty}^{+\infty} \psi^2(\mathrm{t})\mathrm{dt} = 1$—meaning it has a finite length. In addition, the inverse CWT can exist

because of the admissible conditions shown in Equation 3, which are satisfied by the mother wavelet:

$$+\infty > C_\varphi \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\mathrm{w})|^2}{w}\mathrm{dw} > 0 \qquad (3)$$

In Equation 4, ψ(ω) is the Fourier transform of the mother wavelet function ψ(t):

$$\hat{\psi} = (\omega) \int_{-\infty}^{+\infty} \psi(\mathrm{t}) e^{-iw\tau}\mathrm{dt} \qquad (4)$$

ω: the wavenumber containing the Gaussian envelope.

In Equation 5, ω is a single-frequency complex sinusoidal function under the Gaussian envelope:

$$\psi_{w_0}(\mathrm{t}) = \pi^{-1/4}\left(e^{iw_0 t} - e^{-w_0^2/2}\right) e^{\frac{t^2}{2}} \qquad (5)$$

$\pi^{-1/4}$: ensures the Morlet wavelet has unit energy

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$e^{-w_0^2/2}$: ensures the Morlet wavelet satisfies the admissible conditions shown Equation 3

Moreover, when $w_0 \succ 5$, this part of the calculation can be ignored and the Morlet wavelet function simplified as in Equation 6:

$$\psi_{w_0}(t)=\pi^{-1/4}\left(e^{iw_0t}\right)e^{\frac{-t^2}{2}} \qquad (6)$$

$\psi(t)$: the mother wavelet function

ω: the wavenumber, including the Gaussian envelope, that is used to measure the swing times within the cone of influence (COI).

When w_0 is high, the Morlet wavelet has poor localization in the time domain, but better in the frequency domain; when w_0 is low, it has higher and poorer localization in the frequency and time domains, respectively. Therefore, when $w_0 = 6$, Morlet wavelet has better localization in the time and frequency domains. In addition, as the Morlet wavelet is a complex-valued function, if treated as a mother wavelet function, the wavelet transform becomes a complex-valued function as well. Based on the real and imaginary parts of the wavelet transform, amplitude and phase can be calculated and such analysis tools as the wavelet power spectrum, wavelet correlation, and wavelet phase difference can be exported.

3.2. Wavelet Power Spectrum

Using the Morlet wavelet as the mother wavelet, we can obtain the wavelet-transformed value $W(\tau,s)$ and then convert it to the time domain coefficients and frequency. Thus, we can study the mutual relationship between the two time series in the time and frequency domains from the multi-azimuth timescale. If we assume (X,T) and $W_y(\tau,s)$ are the wavelet transforms of two time series X and Y, then the cross-wavelet transform (XWT) can be defined as:

$$Z_{xy}(\tau,\ s\ \tau,\ s) = Z_x(\tau,\ s\ \tau,\ s)Z_y(\tau, s\ \tau, s) \qquad (7)$$

The corresponding cross-wavelet power spectral density indicates a significant correlation with each other. Cross wavelets can describe the relationship between the relative positions of time series X and Y in the time–frequency domain. To calculate the phase difference between these two time series, the mean value of the phase difference and the confidence interval need to be estimated. Disregarding the degree of energy density of the wavelet correlation spectrum and the significant correlation between the corresponding low-energy region of the cross-wavelet power spectrum, the wavelet correlation between the two time series wavelet transform coherence, (WTC) can be defined as shown in Equation 8:

$$|w_{x,y}(\tau,s)|^2 = |w_x(\tau,s)|^2|w_y(\tau,s)|^2 \qquad (8)$$

Through the main frequency corresponding to time (the wavelet power spectrum), the Monte Carlo method can be used to test the wavelet correlation spectrum.

3.3. Wavelet Correlation

Based on the wavelet power spectrum, the time series intersection between x(t) and y(t), and the ratio between the fork and respective wavelet power spectrums can be further used to determine the relationship between x(t) and y(t) in the time and frequency domains (the wavelet coherence coefficient). This is represented by $R_n^2(S)$:

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$$R_n^2(S) = \frac{|s(s^{-1}w_{x,y}(\tau,s)|^2}{s(s^{-1}|w_x(\tau,s)|^2)s(s^{-1}|w_y(\tau,s)|^2)} \quad (9)$$

When $R_n^2(S)$ equals 1, it indicates that x(t) and y(t) are related unconditionally; when $R_n^2(S)$ equals 0, they are not related. According to Torrence and Compo (1998) Monte Carlo simulations can be used to test the significance of the cross-wavelet power spectrum and wavelet correlation coefficients between time series.

3.4. Wavelet Phase Difference

According to Bloomfield *et al.* (2004), the phase difference between time series x(t) and y(t) can be used to determine their lead–lag relationship within a specific time frequency.

Phase difference is defined as the cross-wavelet power Wx, and the imaginary and real ratio of y(τ,s) is as follows:

$$\emptyset(\tau, s) = tan^{-1}\left(\frac{\vartheta\{(\mathrm{Wxy}(\tau,s)\}}{\gamma\{(\mathrm{Wxy}(\tau,s))\}}\right) \quad (10)$$

Among these $\varphi(\tau,s) \in [-\pi, \pi]$ 。

At a specific frequency, the correlation between x(t) and y(t) is as follows:

1. When $\varphi(\tau,s) \in (0,\pi/2)$, x(t) and y(t) are positively correlated and x(t) leads y(t).
2. When $\varphi(\tau,s) \in (\pi/2,\pi)$, x(t) and y(t) are negatively correlated and y(t) leads x(t).
3. When $\varphi(\tau,s) \in (0,-\pi/2)$, x(t) and y(t) are positively correlated and y(t) leads x(t).
4. When $\varphi(\tau,s) \in (-\pi/2,-\pi)$, x(t) and y(t) are negatively correlated and x(t) leads y(t).
5. When $\varphi(\tau,s) = 0$, x(t) and y(t) show a completely positive correlation: with total denaturation.
6. When $\varphi(\tau,s) = \pi$, then x(t) and y(t) show a completely negative correlation.

3.5 Partial Wavelet Coherence and Partial Wavelet Phase Difference

As this study examines the nexus between crude oil and the manufacturing sector, positing that the US and Chinese PMIs are affected by the PPI, this test takes the latter as a control variable. Since China is the largest exporter of crude oil to the United States, the Chinese PMI and PPI, US PMI, and crude oil prices can be used as control variables. Following Aguiar-Conraria and Soares' (2011) wavelet analysis, Equation 11 shows the partial wavelet correlation coefficients of x(t) and y(t) when z(t) represents the control variable:

$$R_{xy|z}^2(\tau, s) = \frac{|R_{xy}(\tau,s) - R_{xz}(\tau,s)R_{yz}^*(\tau,s)|^2}{(1-(R_{xy}(\tau,s)^2)(1-R_{yz}(\tau,s)^2)} \quad (11)$$

$R_{xz}(\tau,s)$ and $R_{yz}(\tau,s)$: the wavelet correlations of x(t) and z(t) and y(t) and z(t), respectively, which are the same when $z(t)$ is a control variable.

As a result, the bias phase difference between x(t) and y(t) is expressed as:

$$\emptyset_{xy|z} = tan^{-1}\left(\frac{\vartheta\{(\mathrm{Cxy|z}(\tau,s)\}}{\gamma\{(\mathrm{Cxy|z}(\tau,s))\}}\right) \quad (.12)$$

$C_{xy|z(\tau,s)}$: the complex partial wavelet coherence, a complex form before removing the absolute value of $R_{xy|z(\tau,s)}$.

4. DATA AND SOURCES

Throughout this study, continuous wavelet transform, wavelet power spectrum, wavelet coherence, and phase difference processing time are used in nonstationary conditions, taking into consideration time and frequency

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domains. Reviewing the overall economy of China and the United States following changes in oil supply and demand, the mother wavelet transform was used to fit the time series and observe the significance of the short- and long-term mutual effects, their relationship, and the phase difference between the lead–lag relationships of the measured variables—including control variables increases the robustness of the tests. The variables adopted were the WTI light crude oil futures prices, the US Institute for Supply Management (ISM) PMI and PPI, and the Chinese PMI and PPI. The monthly data was extracted from DataStream and the *Taiwan Economic News* for a period of 120 months between January 2007 and April 2017.

Table-1. Summary statistics.

Variables	China PMI	US PMI	Oil Price	China PPI	US PPI
Median	51.566	52.107	77.660	0.820	1.937
Mode	51.050	52.600	81.595	0.100	2.250
Max	59.200	59.300	133.88	10.100	10.000
Min	38.800	33.100	29.980	-8.200	-6.900
Std.	2.792	5.0749	23.712	4.772	3.617

Source: DataStream. The sample period from January 2007 to April 2017.

The average value of the US PMI was greater than the Chinese, although the variability of the former was over twice as large as the latter, with the US PMI ranging from a minimum of 33.1 to a maximum of 59.3. In contrast, the variability of the Chinese PPI, ranging from –8.2 to 10.1 was much larger than the US. This indicates that US companies are better able to control the costs of PPI (see Table 1).

5. EMPIRICAL ANALYSIS

5.1. International Crude Oil Prices and Chinese Purchasing Managers' Index (PMI): Using Chinese Producer Price Index (PPI) as Control Variable

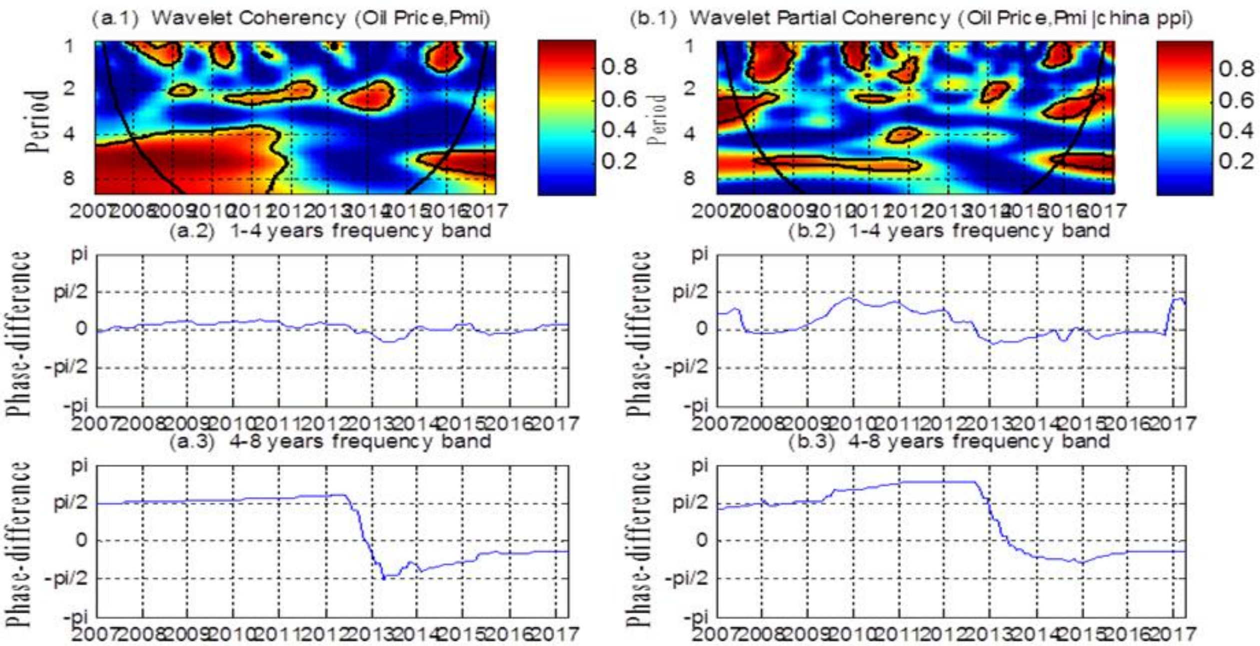

Figure-1. Squared wavelet coherence and phase difference between WTI and Chinese PMI (a.1, a.2, a.3) with Chinese PPI as a control variable (b.1, b.2, b.3). x-axis: time periods; y-axis: scale measured in years; colors: strength of correlation.
Source: DataStream.

Figure 1 represents, on the left, the correlation between international oil prices and the Chinese PMI, and, on the right, the Chinese PPI nexus with these two variables. Taking the left image as an example, Figure (a.1), showing the COI within two symmetric black lines, indicates that the relationship coefficient between those lines is

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easily affected by the edge effect. In addition, the black-outlined colors (variables) demonstrate the significant correlation (at an 80% significance level) (at an 80% significance level) between international oil prices and PMI at specific times and frequencies. The color scale on the right indicates that a higher, and more significant, correlation coefficient between the red-colored variables than the lower and less significant correlation coefficient between the blue-colored variables. Figures (a.2) and (b.2) represent the short-term phase difference (1–4 years), while that in the long term (4–8 years) is shown in Figures (a.3) and (b.3). Figure (a.2) depicts the short-term relationship of international oil prices to PMI between the time and frequency domains: there are significant, positive correlations in 2008–2009, 2010–2011, 2013–2014, and 2015–2016, oil prices leading PMI in the first two periods, but vice versa by the final periods. Figure (a.3) also depicts a long-term significant, positive correlation between oil prices and PMI from 2008 to 2011 and 2015 to 2016, again, with oil prices leading during the earlier period, but vice versa later on. These short-term and long-term perspectives indicate that Chinese PMI was greatly affected by oil prices before 2011, suggesting that managers increased orders while oil prices were low. However, an important structural change occurred after 2015, when Chinese PMI positively led international oil prices in both the short and long term.

After adding the control variable of Chinese PPI, Figure (b.2) shows the short-term relationship of PPI to the WTI crude oil price and Chinese PMI between the time and frequency dimensions: from 2007 to 2008, both moved together; from 2010 to 2012, they were positively correlated, with oil prices leading PMI in the absence of the control variable; while during 2013–2014 and 2015–2016, although still positively correlated, PMI led oil prices. Figure (b.3) shows a long-term significant correlation between oil prices and PMI, in which the former was led by the latter, for both 2008–2012 and 2015–2016; however, whereas the correlation was negative in the earlier period, it was positive later on. Thus, when examining the long- and short-term causal relationship between international crude oil prices and the Chinese PMI after 2013, the latter exerted a positive impact on the former. This is consistent with both Kilian's (2009) and Kaufmann and Ullman's (2009) findings that the rise in international oil prices has little influence over China's high demand for oil. In contrast, other works have revealed that the Chinese PMI was affected by international crude oil price fluctuations (Wu and Li, 2008; Tang and Jiao, 2012) If the PPI control variable is added, then the Chinese PMI will be affected in the short term and driven by demand: an increase in inflation is usually accompanied by economic recovery, which, in turn, raises oil prices. In the long term, though, the results remain the same regardless of whether or not the control variable is included. Owing to China's manufacturing industry being highly sensitive to oil prices, and both structural changes in oil prices and supply exceeding demand after 2014, demand for oil did affected the price (Barsky and Kilian, 2002). China is currently the world's largest energy consumer, and such countries account for 23% of global energy consumption. China showed the largest growth in energy consumption for the 16th consecutive year, while Chinese crude oil production costs remained higher than international crude oil prices.

Table-2. Lead–lag relationship between international crude oil prices and Chinese PMI (with and without the control variable).

Without control variable				
Short term (1–4 years)	2008–2009 OIL positively affects PMI	2010–2011 OIL positively affects PMI	2013–2014 PMI positively affects OIL	2015–2016 PMI positively affects OIL
Long term (4–8 years)	2008–2011 PMI negatively affects OIL		2013–2014 Not significant	2015–2016 PMI positively affects OIL
Control variable (Chinese PPI)				
Short term (1–4 years)	2007–2008 Move together	2010–2012 OIL positively affects PMI	2013–2014 PMI positively affects OIL	2015–2016 PMI positively affects OIL
Long term (4–8 years)	2008–2012 PMI negatively affects OIL		2014–2015 Not significant	2015–2016 PMI positively affects OIL

Source: Figure 1.

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In 2013, China's crude oil imports overtook those of the United States for the first time, and China became the world's largest crude oil importer, with its dependence on foreign oil increasing year on year and oil stock reducing to 65%. The Chinese PMI led oil prices for about half a month, showing how the former directly affects latter; in 2017, Jason Schenker, founder of Prestige Economics, noted that crude oil prices were affected by the demand side of the Chinese PMI (see Table 2).

5.2. International Oil Prices and US-Adopted Institute for Supply Management Manufacturing Purchasing Managers' Index (ISM PMI): Using US Producer Price Index (PPI) as Control Variable

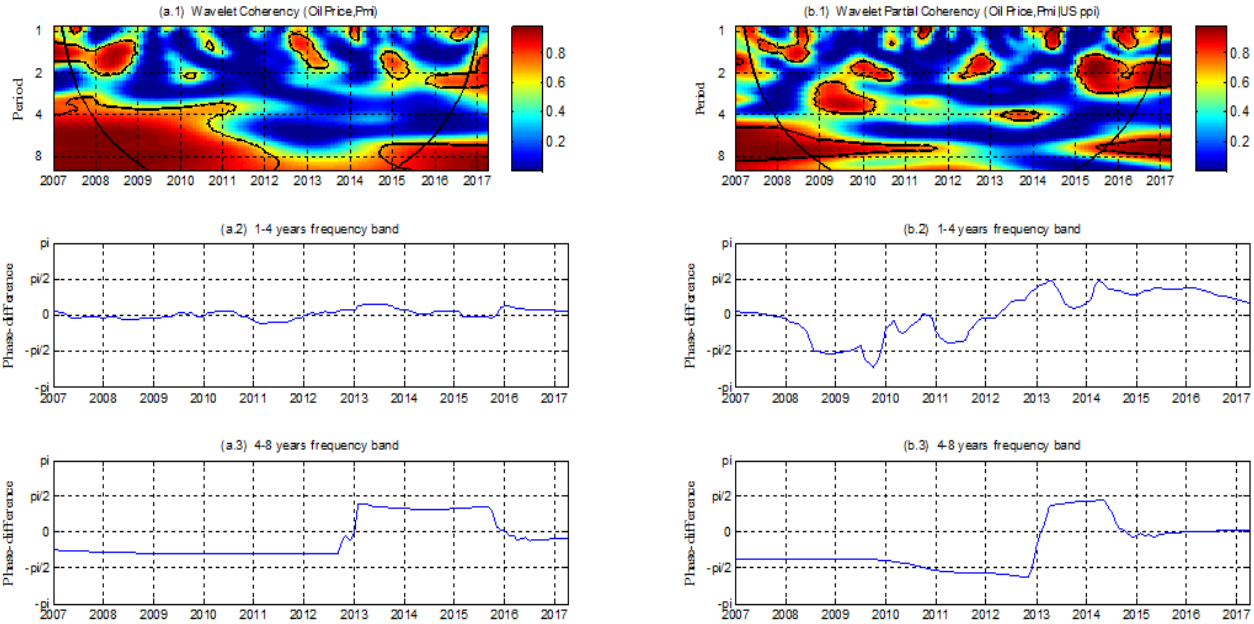

Figure-2. International crude oil prices and US PMI, with US PPI as a control variables

Source: DataStream.

Figure 2 presents the correlation and phase difference between international oil prices and ISM PMI. Figure (a.1) represents the short-term relationship between international oil prices and US PMI in the time and frequency domains. The black-outlined colors for the periods 2007–2009, 2012–2013, and 2015–2016 illustrate the significant, positive correlation between international oil prices and US PMI: from 2007 to 2009, PMI led oil prices, then vice versa during the last two periods. This suggests that oil prices affected US manufacturing after 2012, when large quantities of shale oil were produced in the United States: the higher the oil price, the larger the profit for shale oil companies. In addition, Figure (a.3) shows that, in the long term, international oil prices for 2007–2012 and 2014–2016 were significantly and positively correlated with the PMI, with PMI leading oil prices in the first period, and vice versa in the last. These short-term and long-term perspectives reveal that as US shale oil and gas production increased in the United States, so did the impact of oil prices on the manufacturing industry.

When the US PPI is used as a control variable, Figure (b.2) shows its short-term relationship to international oil prices and PMI in the time and frequency domains for 2007–2008, 2009–2010, 2012–2013, and 2015–2016; these are also evident from the black-outlined colors in Figure (b.1). The correlations are striking: during 2007–2008, PMI was positively correlated to oil prices, but in 2009–2010, following the financial crisis, oil prices led and negatively affected PMI, with the impact continuing over 2012–2013 and 2015–2016. Adding in the control variable, PPI affected oil prices and manufacturing in 2009 and 2010, had little impact afterwards. In the long term, Figure (b.3) shows a significant correlation between international oil prices and PMI in the middle of 2008–2010 and 2011–2012, and early 2015: while PMI positively led oil prices between 2008 and 2010, the impact of European debt on oil prices in mid-2011–2012 negatively affected PMI; from 2013 to 2014, oil prices move ahead of PMI; and then the two variables moved simultaneously in 2015, as shale oil production was expected to revive to reduce the

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transfer of manufacturing overseas. Since US manufacturing is based on the energy industry, shale oil and its provision of abundant low-cost energy increases competition during periods of growth.

Whether or not PPI was affected, in the short term, the upsurge in US shale oil production in 2012 altered the structure of crude oil supply and demand from PMI affecting oil prices to oil prices affecting PMI. From 2013, the United States thus became self-sufficient in crude oil production and crude oil exports escalated, meaning the PPI had little impact. However, in the long term, this changed after 2013 because of the deferred effect of the PPI: in mid-2014, due to the increase in North American crude oil production, oil prices were greatly reduced. According the US Energy Information Administration (EIA) and the International Energy Agency (IEA) report, the trends in supply and demand changes in price of crude oil remain greatly affected by North American crude oil supplies in is forecast to continue changing until 2020; hence, the oil prices are crucial, particularly for the United States to return to manufacturing (see Table 3).

Table-3. Lead–lag relationship between international oil prices and US ISM PMI (with without the control variable).

<table>
<tr><th colspan="5">Without control variable</th></tr>
<tr><td>Short term
(1–4 years)</td><td>2007–2009
PMI positively affects OIL</td><td>2010–2011
Not significant</td><td>2012–2013
OIL positively affects PMI</td><td>2015–2016
OIL positively affects PMI</td></tr>
<tr><td>Long term
(4–8 years)</td><td colspan="2">2007–2012
PMI positively affects OIL</td><td>2012–2013
Not significant</td><td>2014–2016
OIL positively affects PMI</td></tr>
<tr><th colspan="5">Control variable (US PPI)</th></tr>
<tr><td>Short term
(1–4 years)</td><td>2007–2008
PMI positively affects OIL
2009–2010
OIL negatively affects PMI</td><td>2010–2011
Not significant</td><td>2012–2013
OIL positively affects PMI</td><td>2015–2016
OIL positively affects PMI</td></tr>
<tr><td>Long term
(4–8 years)</td><td colspan="2">2008–2010
PMI positively affects OIL
2011–2012
OIL negatively affects PMI</td><td>2013–2014
OIL positively affects PMI</td><td>2015
Move together</td></tr>
</table>

Source: Figure 2.

6. CONCLUSION

This study adopts the wavelet theory model to examine both the Chinese and US PMI and PPI, and the WTI crude oil price between January 2007 and April 2017. The results suggest that, over the decade, the economic competition and manufacturing competitiveness of both countries began to shift. For to period 2008–2012, the Chinese PMI was greatly affected by oil price fluctuations; while in contrast, the US PMI affected oil prices. However, after 2012, especially with the continuous development of shale oil extraction technology in the United States, energy consumption increased rapidly, but its energy self-sufficiency ratio also rose. US crude oil consumption stabilized, though, due to a declining dependence on foreign supplies and thus imports. Conversely, after 2013, China became the largest crude oil importer worldwide, although supplies were greater than demand, meaning oil prices were affected by the Chinese PMI in the long term. This is one of very few studies investigating how oil prices have been affected across different time periods between the United States and China. It demonstrates that while the US PMI affected oil prices between 2007 and 2012, the Chinese PMI exerted such an effect after 2013. It also reveals a structural change in oil prices and its role in the market between China and the United States.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.
Acknowledgement: Both authors contributed equally to the conception and design of the study.

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