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Impacts of international oil price fluctuations on China's PM2.5 concentrations: a wavelet analysis

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ABSTRACT

In the past few years, China's air quality, particularly PM2.5 concentrations, has received extensive attention. China is increasingly dependent on imported oil, and the international oil price fluctuations influence the air quality by two paths. A rise in oil prices puts pressure on the economy and reduces energy consumption, which could improve air quality. However, the substitution effect by high oil prices tends to increase the use of environmentally unfriendly energies, which worsens air quality. In this study, the authors employ wavelet analysis to determine how international oil price fluctuations affect PM2.5 concentrations in China. The authors process a sample of 12 typical Chinese cities, which are discretely distributed in the northeast, north, east, central, south, and southwest of China. The results show that in most cities international crude oil prices are positively correlated to the PM2.5 concentrations in the short term (1–4 months) and that the fluctuations in oil prices are usually ahead of the changes of PM2.5 concentrations. It is more pronounced in industrially developed cities such as in Shanghai. An extension of the study to include the country data yields more consistent findings. Empirical analysis indicates that, in the short run, the substitution effect caused by oil price fluctuations exerts a stronger impact on PM2.5 concentrations.

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1. Introduction

Oil is considered an extremely critical strategic resource around the world. According to the National Bureau of Statistics, over 65% of China's oil was imported in 2016, making China the world's largest oil importer. Inevitably, international oil prices are increasingly affecting the economy, politics, and people's lives in China. Besides, oil prices can indirectly affect the air quality by changing the energy utilisation, especially in oil-consuming countries. Specifically, when international oil prices fluctuate, not only the economy but also air quality are under serious influence owing to China's

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heavy dependence on imported oil. Air pollution is a serious challenge in China's development process. The Health Effects Institute reports that long-term exposure to ambient PM_{2.5} contributed to 4.1 million deaths in 2016. India (25%) and China (26%) together account for more than half of the mortality burden attributable to PM_{2.5}. PM_{2.5} (particulate matter with an aerodynamic diameter less than 2.5 μm) is a carcinogen that can float in the air for a long time. In 2011, it was reported as the main culprit causing haze, and hit China. Nowadays, the concentration of PM_{2.5} is a vital air pollution indicator familiar to the public. Much research reveals that the fossil fuel combustion, biomass burning, dust and traffic are important and direct sources of PM_{2.5} (Ru-Jin, Yanlin, & Carlo, 2014). We try to find the indirect but equally crucial economic factor, international oil prices. In this study, we figure out the relationship between international oil prices and PM_{2.5} concentrations by comparing two different paths by which international oil price fluctuations affect the PM_{2.5} concentrations of China. It is a meaningful complement and extension to existing research and the results are significant for policy-makers when they want to achieve a balance between economic development and environmental protection.

According to income effect and substitution effect, oil prices can indirectly influence the air quality by changing the amount and structure of China's energy consumption. The two paths of high international oil prices affecting air quality are shown in Figure 1. At first, the rising price reduces oil consumption and increases the production cost of many commodities (Boschi & Girardi, 2011), which is detrimental to the economy. Hamilton James (1983) proves that the oil shock is a contributing factor to some of the economic recessions in the U.S. before 1972. However, the decrease in oil consumption caused by the high oil prices tends to reduce air pollution. When oil prices decline, the economy and total energy consumption increase, resulting in greater pressure on the environment. The path of air quality being affected by the economy and total energy consumption is called the macro effect. In addition, as oil prices increase, the substitution effect should not be ignored. Normally, the higher oil prices are likely dramatically to drive people to use low-cost alternative energies, although they cause more serious environmental pollution.

But how strong are the macro effect and substitution effect caused by the international oil price fluctuations? Further, affected by the two diverse effects, what will China's air quality be? These issues need to be considered in the context of China's national conditions. In fact, the imported oil demand is price inelastic in China. In the past few years, China's output and total energy consumption have maintained

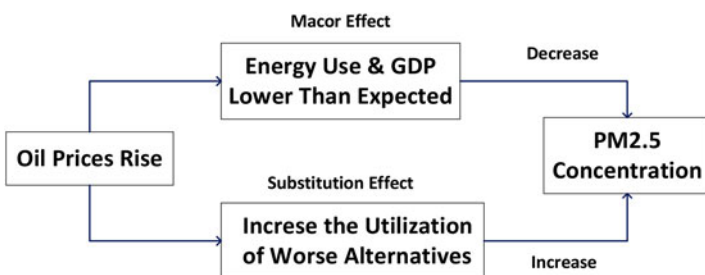


Figure 1. Two different paths by which oil prices increase affect the PM 2.5 concentrations. Source: Authors' calculation.

rapid growth, and seem immune to oil price fluctuations. Employing the VAR model, Shi (2016) finds that Chinese crude oil imports are hardly influenced by price but are determined by China's economic growth. Thus, the reduced consumption of fuels caused by the high price is not enough to improve the air quality a lot. It is the real reason that some studies concluded that oil prices are not related to PM2.5 in many Chinese cities. Meanwhile, the substitutions are widespread in industries, traffic and daily life. Heavy fuel oils are relatively easy to replace (Alabdulhadi, 2014), which are a large part of imported oil in China. Besides, China's industry is built on coal, keeping a relatively large replacement space between coal and oil. This space will be more packed when the oil is much more expensive. Even with several technical limitations, many sectors use inferior oil instead of high-quality oil to reduce costs, which increases emissions hugely. In traffic, fuel vehicles are the mainstream in China, according to reports from NGV Global, to June 2018, China's natural gas vehicles account for only 3.73% of the country's car ownership. The oil quality in China is two to three levels lower than in developed countries all the time, and many private gas stations provide more inferior, cheaper oils. Facing the high price of oil, private car use is reduced, but those inferior oils are more popular too, especially among truck drivers. Many trucks without qualified exhaust gas treatment were often driven at night in order to avoid supervision, causing major air pollution in traffic. Compared with the above two aspects, the total amount of PM2.5 emitted by households is tiny, but the obvious substitution effect still exists. It is very common that people reduce the use of the more expensive liquefied petroleum gas but increase the burning of coal, even firewood in rural areas of China. The increasing electricity consumption by rural and urban residents mostly comes from coal-fired power stations in the end. The substitution effect means when oil prices rise high-quality oils are gradually replaced by inferior energies in many aspects, resulting in the deterioration of air quality. Considering these special national conditions of China, we believe that when international oil prices fluctuate, the substitution effect may be more effective than the macro effect. But existing studies show different conclusions. With a simple statistical analysis of the 2014 monthly data, the PM2.5 concentrations from the U.S. Consulates, Dan-Ping et al. (2017) prove that the changes of PM2.5 concentrations in Beijing, Shanghai, and Guangzhou have little connection with domestic oil price changes. Ma and Wei (2016) provide a rational empirical framework, constructing a dynamic computable general equilibrium (CGE) model from the 2012 input-output table, and point out that the rise in oil prices cannot effectively reduce the PM2.5 concentrations. These studies employ traditional statistical analysis or different models, analysing a few districts of China, and get differing conclusions.

The present study uses wavelet analysis to determine how international oil price fluctuations affect China's air quality. Wavelet analysis gradually becomes popular in economics and finance (Cascio, 2015; Jiang, Chang, & Li, 2015). To our knowledge, no previous research has employed wavelet analysis to study the relationship between oil prices and air quality. We hope to take full advantage of it and to determine the real relationship between international oil price fluctuations and China's PM2.5 concentrations.

The main contributions of our study are as follows. First, based on the theoretical framework and China's national conditions, we put forward several reasonable

assumptions on how international oil price fluctuations affect China's air quality and obtain novel results through empirical research. Second, wavelet analysis decomposes the data into sinusoidal components of various frequencies, which makes it possible to provide more information from time and frequency domains simultaneously. At the same time, we expand the application of wavelet analysis. Third, different from previous research, the data used in this study are more comprehensive, covering many districts and a longer time. To reach more realistic conclusions, we analyse 12 cities and the macro data, the latter from 74 cities. Finally, based on our results, some effective suggestions for improving air quality of China are proposed.

The rest of the paper is organised as follows. [Section 2](#) briefly reviews the related literature. Sections 3 and 4 provide an overview of data and methodology, respectively. The fifth section outlines the empirical application and the discussion and conclusion are presented in the final section.

2. Literature review

Oil as a vital input and raw material in the world directly influences the costs of production (Sodeyfi & Katircioglu, 2016), which also affect a lot of economic subsectors simultaneously. There are abundant studies focusing on the connections between oil prices and the development of various industries, such as agriculture (Gokmenoglu, Bekun, & Taspinar, 2016), service trade and tourism (Katircioglu, 2017), and finance (Katircioglu, Katircioglu, & Altun, 2018; Shaeri, Adaoglu, & Katircioglu, 2016). Most of them reveal that high oil prices exert negative effects on the development of several important industries, especially for oil-importing countries. This impact of oil prices on economic subsectors is going to be reflected in the macroeconomy. Korhonen and Ledyeva (2010) assessed the impact of oil price shocks on oil-producer and oil-consuming economies. The conclusions obtained in their study are consistent with expectations. That is, oil producers (Russia and Canada) benefit from oil price shocks while the largest negative effects are found in the main oil-consuming countries (Japan, China, the U.S., Finland and Switzerland). Katircioglu, Sertoglu, Candemir, and Mercan (2015) also investigate the effects of oil prices on macroeconomic performance. The results of their study reveal that the price of oil exerts negative and significant impacts on several other macroeconomic variables, including gross domestic product (GDP) in the case of Organisation for Economic Cooperation and Development countries.

More than 20 years ago, some research in environmental economics proposed a tight relationship between economic development and environmental protection (Grossman & Krueger, 1991; Panayotou, 1997). As a matter of fact, there seems to be an irreconcilable contradiction between economic development and environmental protection in most developing countries. Wang, Yang, Wang, and Song (2017) found that the relationship between the economic index (GDP per person) and environmental index (CO₂ emissions) is an approximately linear curve other than an inverted U-shaped in China. Given the close connections between the economy and the environment, it is appropriate and necessary to study the impact of oil price movements on environmental indicators. Katircioglu (2017) adds the oil price in the test of the conventional environmental Kuznets curve. Some other studies explore the

impact of oil price movements on carbon dioxide emissions (Henriques & Sadorsky, 2008; Méjean & Hope, 2013; Sadorsky, 2009).

Although there is an increasing number of studies about the impacts of oil prices on CO₂ emissions, the literature on the connection between oil prices and PM2.5 is limited. The issue is vital, particularly for the main oil-consuming countries with serious air pollution. The existing research on this topic scarcely analyse enough data and give different conclusions (Ma & Wei, 2016; Dan-Ping et al., 2017). The purpose of this study is to investigate the interactions between international oil prices and PM2.5 concentrations in China; we take the GDP as control variable in order to avoid omitted variable bias. The method used in this study is wavelet analysis, which is employed widely in studies about oil prices too (Akoum, Graham, Kivihaho, Nikkinen, & Omran, 2012; Uddin, Tiwari, Arouri, & Teulon, 2013). To the best of our knowledge, this study is the first of its kind to investigate the relationship between oil prices and PM2.5 concentrations using the wavelet analysis.

3. Data descriptions

The data used in this study are monthly figures including PM2.5 concentrations (micrograms per cubic metre), international crude oil prices (dollars per barrel), GDP (renminbi billions), and Sino–U.S. exchange rates. The PM2.5 concentrations, international crude oil prices, and GDP were taken as the dependent variable y , independent variable x , and control variable z , respectively.

The China National Environmental Monitoring Centre released 74 cities' monthly PM2.5 concentrations from December 2013 to December 2017. We rank the total of PM2.5 concentrations in the past 5 years in ascending order, and, in terms of geographical distribution, and economic factors, select 3 groups of 12 cities as research objects out of the 74 cities. In order to obtain more general results, the country data, from January 2013 to December 2017, are also be analysed. In the country data, the average of PM2.5 concentrations in 74 cities is taken as the PM2.5 concentration of China, which is appropriate because the 74 cities announced by the China Environmental Monitoring Centre formed a network covering 31 provincial-level administrative regions.¹ The corresponding quarterly GDP figures are given by China's National Bureau of Statistics; the cubic interpolation method is used to obtain the monthly fitting values. The Europe Brent Spot Oil Price Free On Board (FOB) is from the U.S. Energy Information Administration and the Sino–U.S. exchange rate is collected from the U.S. Board of Governors of the Federal Reserve System. Table 1 summarises the statistical properties of raw data including the Europe Brent Spot Oil Price FOB and PM2.5 concentrations for each city and the country. All the variables are converted into a unified unit according to the exchange rate. The logarithms of all data are taken to correct for potential heteroscedasticity and dimensional differences between the series.

4. Methodology

The time series contains the information not only in time but also in frequency domains. As an upgrade to the well-known Fourier analysis, wavelet analysis can

Table 1. Descriptive statistics for raw data.

	Min.	Max.	Mean.	Std dev.	Skewness	Kurtosis	Observations
Panel A: international crude oil price FOB from January 2013 to December 2017							
Oil_P	30.7	116.05	71.56	28.30	0.3975	1.4529	60
Panel B: 12 cities' monthly PM2.5 concentrations from December 2013 to December 2017							
Ningbo	20	135	43.347	20.576	2.102	9.337	49
Dalian	16	93	43.449	16.865	0.758	3.261	49
Xiamen	14	53	30.408	9.476	0.363	2.635	49
Guangzhou	18	90	40.429	14.058	1.336	5.677	49
Qingdao	18	106	49.204	21.241	0.837	3.285	49
Hohhot	18	102	43.694	19.257	0.797	3.026	49
Shanghai	19	125	48.735	18.167	1.624	7.770	49
Yangzhou	22	149	58.204	23.964	1.255	5.709	49
Wuhan	23	183	67.265	35.116	1.386	5.397	49
Jinan	37	160	81.326	28.050	0.933	3.460	49
Harbin	16	155	64.980	41.806	0.663	2.144	49
Beijing	38	152	74.061	27.163	1.110	3.725	49
Panel C: national monthly PM2.5 concentrations from January 2013 to December 2017							
Country	27	130	57.102	22.131	1.192	4.561	60

Source: WIND database.

extract localised information in both time and frequency domains. Moreover, compared with traditional methods, wavelet analysis is suitable for non-stationary or locally stationary series (Roueff & Sachs, 2011). Wavelet transform decomposes the original time series into some basis wavelets obtained by position shifting and scaling of the same mother wavelet. Therefore, the time series is expanded into a time–frequency space where its oscillations can be observed in a highly intuitive way. There are two popular methods of wavelet transform: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). The DWT is applicable for noise reduction and data compression, whereas the CWT is more powerful with respect to feature extraction and data self-similarity detection (Grinsted, Moore, & Jevrejeva, 2004; Loh, 2013). Therefore, we mainly use several CWT tools in this study; an introduction of it is given below.

4.1. Continuous wavelet transform

The definition of a continuous wavelet is:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t) \psi_{\tau, s}^*(t) dt \quad (1)$$

where $x(t)$ is the time signal, the asterisk denotes the complex conjugate, and $\psi_{\tau, s}^*(t)$ is the complex conjugate function of $\psi_{\tau, s}$, which is the so-called basis wavelet function. The basis wavelet is a sequence of functions obtained by scaling and translating the mother wavelet $\psi(t)$. The relationship between $\psi_{\tau, s}$ and $\psi(t)$ can be expressed as: $\psi_{\tau, s} = (1/\sqrt{s}) \psi[(t - \tau)/s]$; s is referred to as the scaling or dilation parameter, and determines the width of the wavelet and the frequency resolution; the variable τ is called the location or translation parameter and controls the location. Various mother wavelets are available for different purposes, such as the Haar, Morlet, Mexican hat, and so on. The wavelet used in this study is the Morlet wavelet, which is popular for feature extraction and represented as (Grossmann & Morlet, 1984):

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-\omega_0^2/2} \quad (2)$$

where $\pi^{-1/4}$ ensures the unity energy of the Morlet wavelet and $e^{-\omega_0^2/2}$ makes it satisfy the admissibility condition of Equation (3); here, ω_0 is the central frequency of the wavelet. Normally it is equal to six to ensure that the Morlet wavelet achieves an optimal trade-off between time and frequency localisation (Grinsted et al., 2004).

The mother wavelet function, $\psi(t)$, must meet three conditions. First, its mean value must be zero, that is, $\int_{-\infty}^{+\infty} \psi(t) dt = 0$, which ensures its oscillation across positives and negatives and being non-zero locally. Second, the square integral of the mother wavelet must be equal to unity, that is, $\int_{-\infty}^{+\infty} \psi(t)^2 dt = 1$, which denotes a limitation to an interval of time. Third, it must satisfy the admissibility condition, which can be represented as:

$$0 < C_\psi = \int_0^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega < +\infty \quad (3)$$

The Fourier frequency f is given by $f(s) = \omega_0/2\pi$ (Aguiar-Conraria & Soares, 2014), and for the best choice of $\omega_0 = 6$ the convention from s to f occurs in the sense that:

$$f = 6/2\pi s \approx 1/s \quad (4)$$

The wavelet scale s approximates a reciprocal of the Fourier frequency f , which means that $x(t)$ is decomposed into a joint time–frequency plane where the shorter (longer) wavelet scale corresponds to the higher (lower) frequency.

4.2. Wavelet coherency and phase difference

Wavelet coherency considers the time and frequency components at the same time, as well as the strength of correlation between the time series components (Loh, 2013). It is applicable to observe both the time and frequency variations of the correlation between series in a time–frequency space. Therefore, the wavelet coherency supplies a better measure of co-movements between the international oil prices and the PM2.5 concentrations of China in comparison with the conventional correlation analysis. Following the approach of Torrence and Webster (2010), we estimate wavelet coherency by using the cross-wavelet and auto-wavelet power spectrums as follows:

$$R_{xy}^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau, s))|^2}{S(s^{-1}|W_x(\tau, s)^2)S(s^{-1}|W_y(\tau, s)^2)} \quad (5)$$

In the formula above, S is a smoothing operator for performing time–frequency normalisation processing. The value of $R_{xy}^2(\tau, s)$ is between zero and one, zero coherency indicates no co-movement between the oil prices and PM2.5 concentrations, while the highest coherency implies the strongest co-movement between the two variables. In the empirical part, we also mark the squared wavelet coherency with colours

in the wavelet coherency plots, where red and blue colours correspond to strong and weak co-movements, respectively.

The wavelet coherency is squared, which cannot distinguish between positive and negative co-movements. Therefore, the phase difference is subsequently employed to provide information on positive and negative co-movements as well as the lead-lag relationships between the two variables. According to Bloomfield et al. (2004), the phase difference characterises the phase relationship between $x(t)$ and $y(t)$ such that:

$$\phi_{xy} = \tan^{-1} \left[\frac{\Im(W_{xy}(\tau, s))}{\Re(W_{xy}(\tau, s))} \right], \quad \phi_{xy} \in [-\pi, \pi] \quad (6)$$

where \Im and \Re equal the imaginary and real parts of the smoothed cross-wavelet transform, respectively. A phase difference of zero means that the two series move together while a phase difference of $\pi(-\pi)$ implies that they move in the opposite directions. If $\phi_{xy} \in (0, \frac{\pi}{2})$, the series move in phase (positively co-move) and $x(t)$ leads $y(t)$. If $\phi_{xy} \in (\frac{\pi}{2}, \pi)$, the series move out of phase (negatively co-move) and $y(t)$ is leading. If $\phi_{xy} \in (-\frac{\pi}{2}, 0)$, then the series move in phase with $y(t)$ leading $x(t)$. If $\phi_{xy} \in (-\pi, -\frac{\pi}{2})$, then the series move out of phase with $x(t)$ leading $y(t)$. The phase difference can also indicate causality between $x(t)$ and $y(t)$ in the time and frequency domains. As a result, it dominates the conventional Granger causality test, which assumes that a single causal link holds for the whole sample period as well as at each frequency (Grinsted et al., 2004; Tiwari, Mutascu, & Andries, 2013). For instance, in wavelet analysis, if $x(t)$ leads $y(t)$, then a causal relationship runs from $x(t)$ to $y(t)$ at a particular time and frequency.

Given that economic fundamentals could be related to both the oil prices and the air quality, we therefore want to eliminate the effects of economic performance to uncover the real co-movement and causality between the two returns. For this purpose, we rely on partial wavelet coherency and partial phase difference extensions of wavelet coherency and phase difference, respectively. According to Aguiar-Conraria and Soares (2014), they are defined as:

$$R_{xy|z}^2(\tau, s) = \frac{|R_{xy}(\tau, s) - R_{xz}(\tau, s)R_{yz}^*(\tau, s)|^2}{(1 - (R_{xy}(\tau, s))^2)(1 - (R_{yz}(\tau, s))^2)} \quad (7)$$

where $R_{xz}(\tau, s)$ and $R_{yz}(\tau, s)$ indicate the wavelet coherencies between $x(t)$ and $z(t)$ and between $y(t)$ and $z(t)$, respectively. Further, the partial phase difference is represented as:

$$\phi_{xy|z} = \tan^{-1} \left(\frac{\Im(C_{xy|z}(\tau, s))}{\Re(C_{xy|z}(\tau, s))} \right) \quad (8)$$

where \Im and \Re equal the imaginary and real parts of the complex partial wavelet coherency $C_{xy|z}(\tau, s)$, respectively. The complex partial wavelet coherency, as the name implies, is the complex type of $R_{xyz}(\tau, s)$ before taking the absolute value.

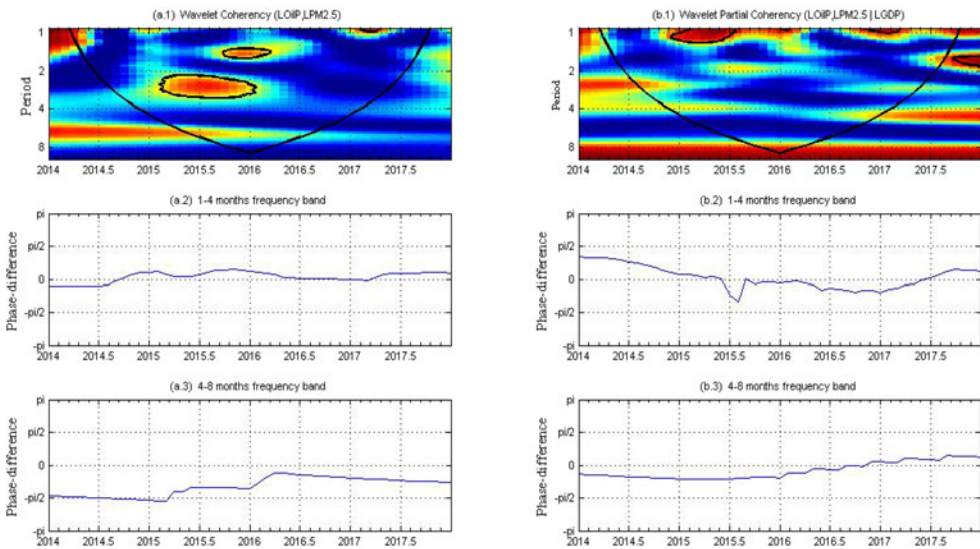


Figure 2. Ningbo (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

5. Empirical results

Figures 2–14 show the results of the wavelet analysis. The left side of these figures represents the wavelet coherence (a.1) and phase difference for two different frequency bands ((a.2) and (a.3)), corresponding to cycles of 1–4 and 4–8 months, respectively. The right side contains the partial wavelet coherence (b.1) and partial phase difference, (b.2, 1–4 months) and (b.3, 4–8 months). Compared with the left, the control variable z is processed in the partial wavelet coherence, which reveals more precise results. Normally, the results on the left are used for reference. Note that the thick black lines in the wavelet power spectrum plots designate the 5% significance level estimated from Monte Carlo simulations using a phase randomised surrogate series.² The regions below the thin black lines are cones of influence (COI) in which edge effects exist. The continuous wavelet transform Toolbox employed in this paper is provided by Aguilar Conraria and Soares (2014) is employed. As mentioned before, the wavelet power spectrum is an indicator of the local volatility of underlying series; and the colour code for power ranges from blue, which represents low power, to red, which represents high power.

5.1. Cities' results

In the city samples, the x -axis refers to the time period from December 2013 to December 2017 and the y -axis refers to the frequencies, measured in months. The first group with the lowest PM2.5 concentrations contains four cities, namely, Ningbo, Dalian, Xiamen, and Guangzhou, which are all located in coastal areas. In Figure 2(b) we can see, in Ningbo, from October 2014 to May 2015, the oil prices are positively correlated to PM2.5 concentrations in the shorter cycles (1–4 months) and x leads y ;³ however, from October 2016 to February 2017 it shows an inverse

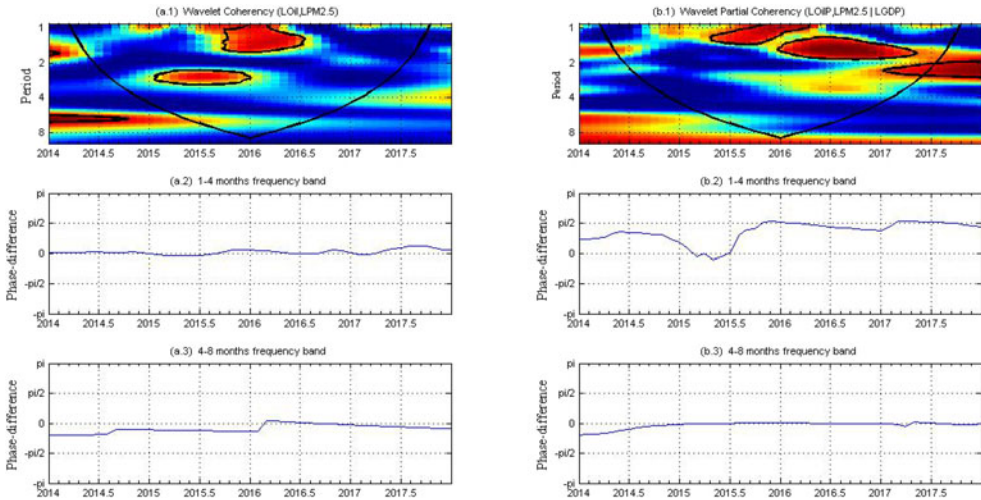


Figure 3. Dalian (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

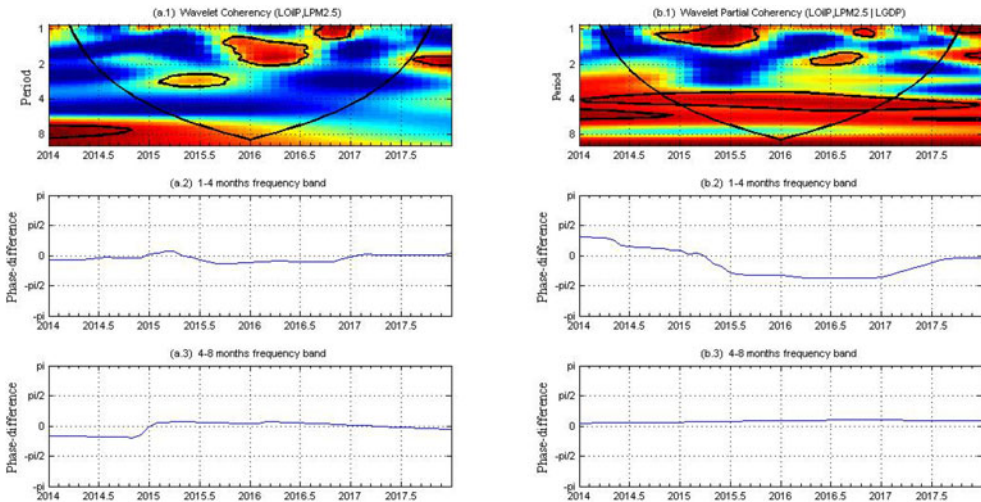


Figure 4. Xiamen (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

consequence. During this period, y is leading x . Considering that the PM2.5 concentrations can barely affect international oil prices, y leading x is meaningless. As a sub-provincial city in the Zhejiang Province, Ningbo has the largest deep-water port in China. Its industry and foreign trade are developing quickly, ranking second in GDP among the cities of Zhejiang Province. Ningbo itself lacks energy, and its huge energy demand depends mainly on external support. Apparently, with a booming economy, the environment in Ningbo is naturally under greater pressure. From June 2015 to March 2017, [Figure 3\(b\)](#) reveals a significant positive correlation between x and y in 1–4 months frequency, and x is leading. Like Ningbo, Dalian has many excellent

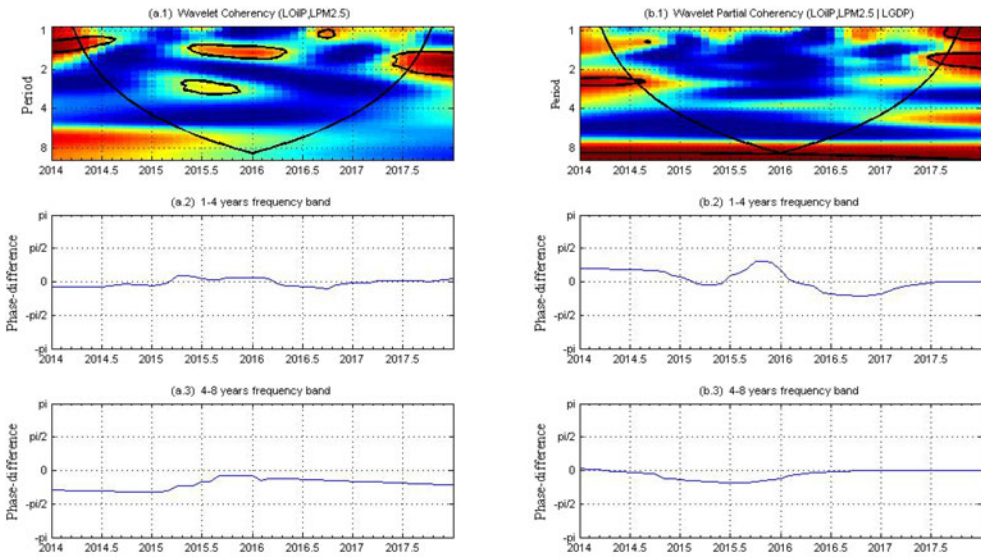


Figure 5. Guangzhou (a.1) wavelet coherency; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherency; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors’ calculation.

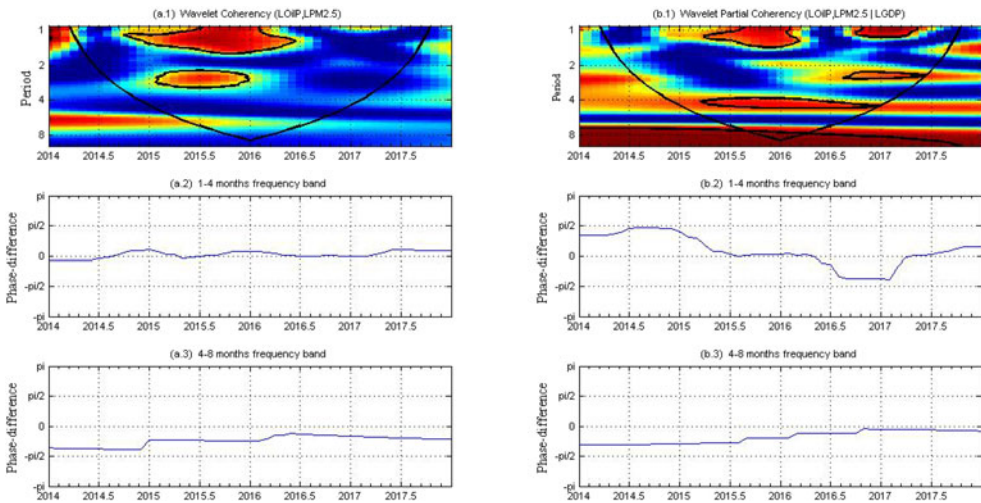


Figure 6. Qingdao (a.1) wavelet coherency; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherency; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors’ calculation.

ports, but its location is in northeast China. As a sub-provincial city in the Liaoning Province, Dalian is known for its developed heavy industries, which means it causes severe air pollution through its consumption of a large amount of fossil energy every year. However, Dalian controls environmental pollution vigorously. In 2017, its air quality ranked first in the northern key cities. Figure 4 shows that the oil prices in Xiamen are positively correlated to the PM2.5 concentrations over the period September 2014–March 2015, and that the former is leading. The corresponding city,

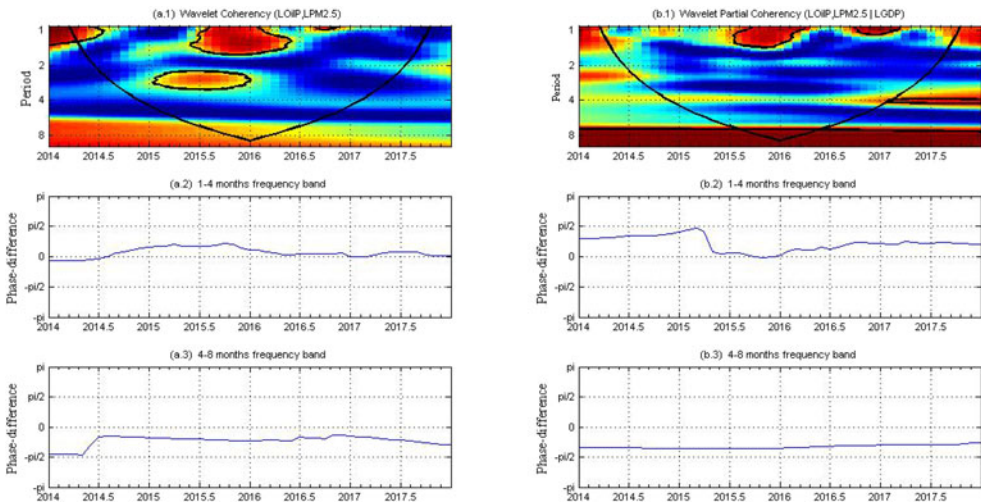


Figure 7. Hohhot (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

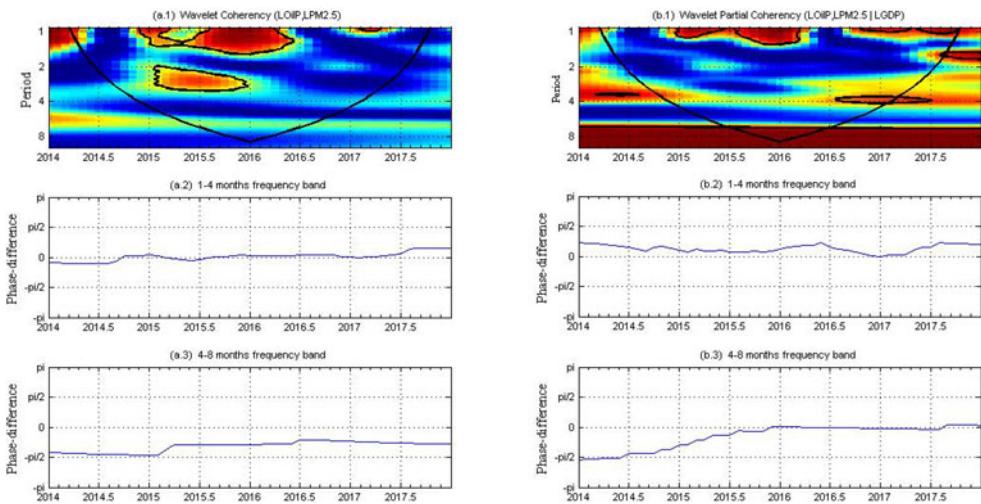


Figure 8. Shanghai (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

Xiamen, is a regional economic and cultural centre, and its per capita GDP ranks first in Fujian Province. Xiamen's pillar industries are environmentally friendly industries and tertiary industry, so its fossil energy demand is not big. The partial wavelet coherence in Figure 5(b) shows no relationship between the PM2.5 concentrations and oil prices, which may be attributed to Guangzhou's location and climate. Guangzhou is a super-large city with an export-oriented economy, whose permanent population exceeded 14 million at the end of 2017. However, the city is located on the southeast coast of China, with a subtropical monsoon climate and rich precipitation, and its PM2.5 concentrations are always relatively low and devoid of changes.

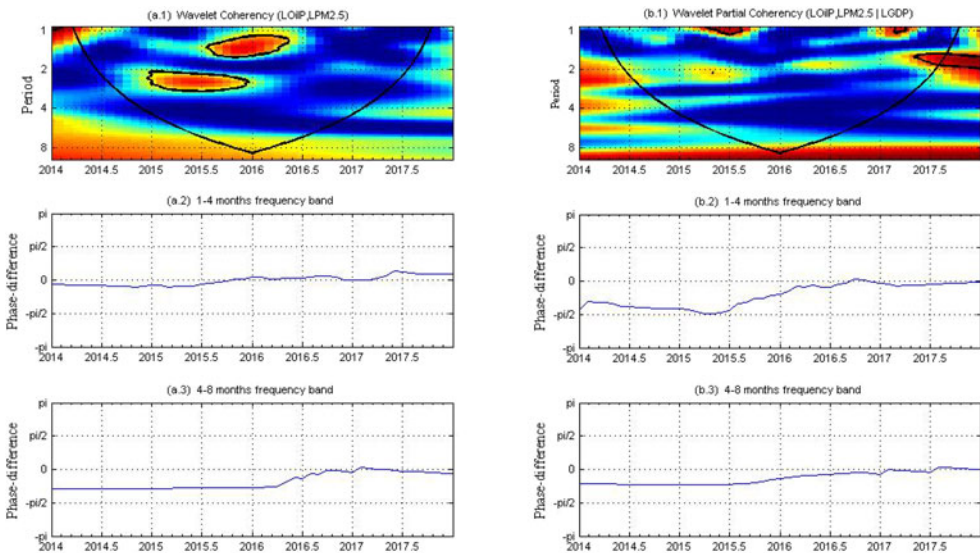


Figure 9. Yangzhou (a.1) wavelet coherency; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherency; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

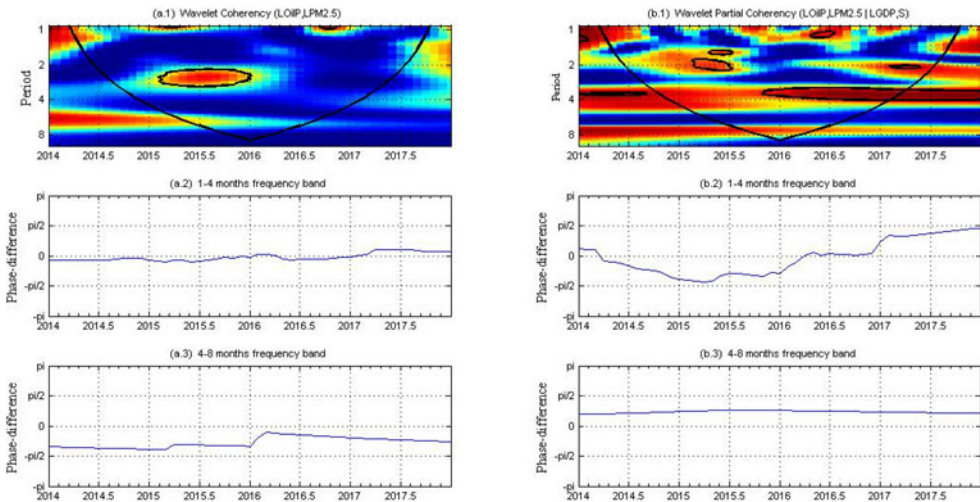


Figure 10. Wuhan (a.1) wavelet coherency; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherency; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

The second group, with a moderate PM2.5, includes Qingdao, Hohhot, Shanghai and Yangzhou. Figure 6 indicates a positive correlation between oil prices and PM2.5 concentrations in Qingdao. From January to June 2015, x leads y at 1–4 months frequency. Conversely, from May 2015 to December 2017, y is leading at 4–8 months frequency. As indicated above, this does not mean that the PM2.5 concentrations are the cause of international oil price fluctuations. Qingdao is located at the southern tip

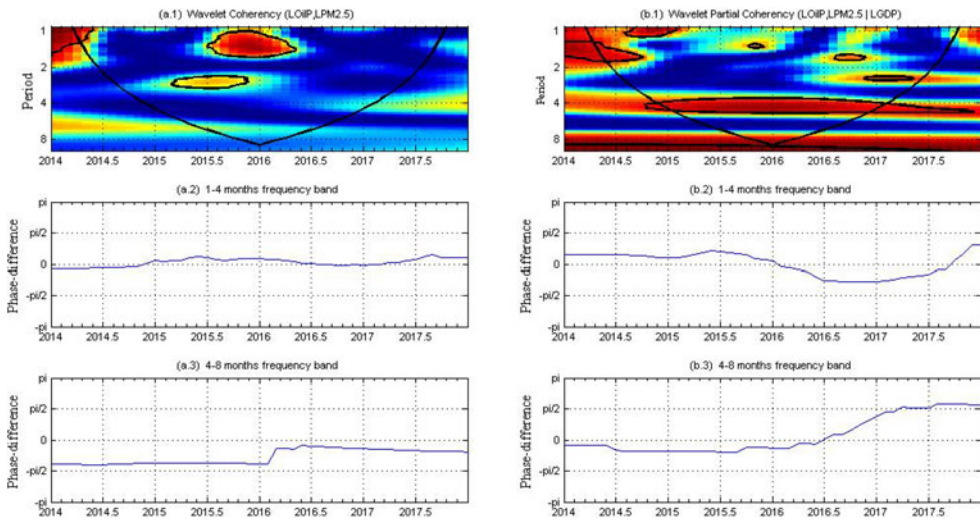


Figure 11. Jinan (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

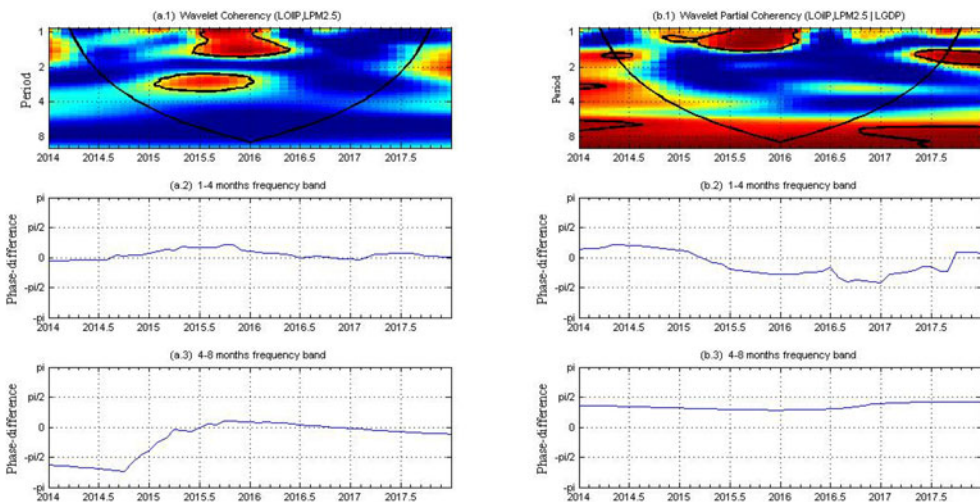


Figure 12. Harbin (a.1) wavelet coherence; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherence; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

of the Shandong Peninsula. The superior geographical location has made Qingdao a famous tourist attraction. However, with the rapid economic development, pollutant emissions have increased a lot. Figure 7(b) indicates that x is leading y in Hohhot at 1–4 months frequency, from June 2016 to February 2017. Hohhot is the capital of the Inner Mongolia Autonomous Region, whose economy is dominated by the wool textile, animal husbandry, power, chemical, and tourism industries. It is an inland city with an annual precipitation below 600 mm, which is not conducive to air cleaning.

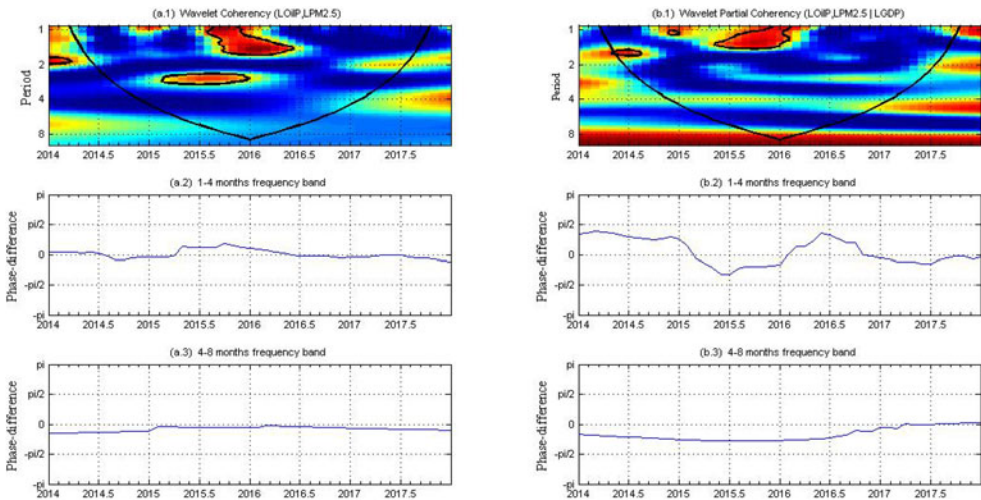


Figure 13. Beijing (a.1) wavelet coherency; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherency; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

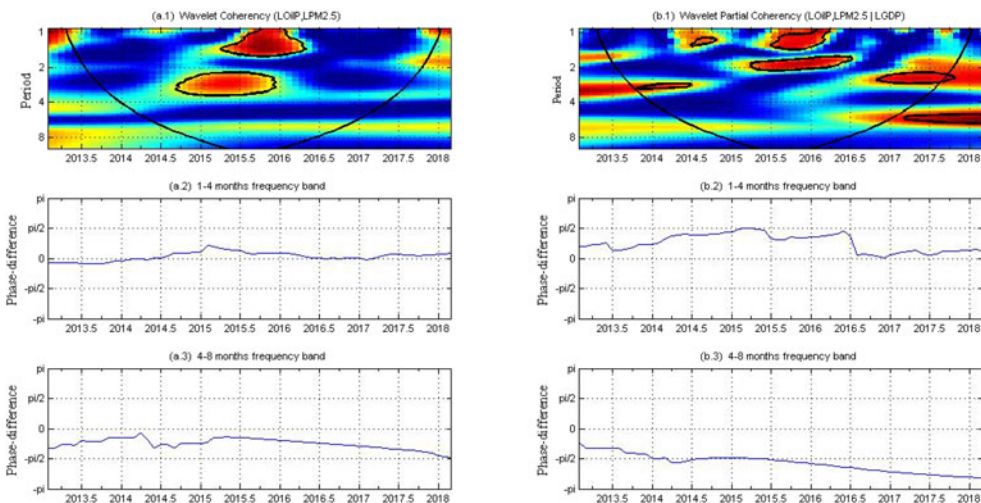


Figure 14. Country data of 74 cities: (January 2013–March 2018) (a.1) wavelet coherency; (a.2) and (a.3) phase difference for the 1–4 months and 4–8 months frequency bands, respectively. (b.1) Partial wavelet coherency; (b.2) and (b.3) partial phase difference for the 1–4 months and 4–8 months frequency bands, respectively. Source: Authors' calculation.

Similar results can be observed in Shanghai. [Figure 8](#) indicates that the oil prices lead the PM_{2.5} concentrations at 1–4 months frequency from November 2014 to February 2016 and June 2016 to February 2017. As a municipality and economically developed city of China, Shanghai consumes a significant amount of external energy, while simultaneously causing serious environmental pollution. The results revealed by [Figure 9\(b\)](#) resemble those of Guangzhou, that is, the international oil prices have nothing to do with PM_{2.5} concentrations. Yangzhou was named one of the world's best cities

to live in by the United Nations in 2006. Located in central Jiangsu Province, it is a typical Jiangnan water town with prosperous tourism. Owing to severe environmental regulations and a favourable climate, PM2.5 concentrations in Yangzhou are constant and relatively low. In the second group, the former three cities are in good agreement with theoretical expectations, especially Shanghai and Hohhot.

The cities of the third group, with the heaviest PM2.5, are Wuhan, Jinan, Harbin and Beijing. [Figure 10](#) shows that the international oil prices in Wuhan are leading from March 2016 to February 2017, and that the two variables are positively correlated at 1–4 months frequency. Wuhan is the capital of Hubei Province. In recent years, with a revival plan proposed, the industrial and infrastructure construction boom has exerted great pressure on the environment. From March 2014 to January 2016 in Jinan ([Figure 11\(b\)](#)), x leads y at 1–4 months frequency; however, y is leading at 4–8 months frequency from December 2014 to June 2016. In 2017, the share rates of motor vehicles, coal, dust, and industrial production contributing to PM2.5 in Jinan, the capital of Shandong province, were 32.6, 24.6, 14.6, and 14.5%, respectively. In addition, Jinan is surrounded by mountains on three sides and has poor air mobility, which is not conducive to the diffusion of air pollutants. [Figure 12\(b\)](#) shows that, from April to June 2014 and September to February 2015 in Harbin, x leads y at 1–4 months frequency. Because of the poor quality of coal used in industry and heating, Harbin, the capital of Heilongjiang Province, once suffered from severe air pollution for many years. The last city, Beijing, is called the ‘foggy city’ due to severe smog. From April 2014 to August 2014, and from May 2015 to June 2015 ([Figure 13\(b\)](#)), the oil prices in Beijing are positively correlated to the PM2.5 concentrations, and x leads y at 1–4 months frequency. As the capital of China, the poor air quality in Beijing rouses great concern. Its air pollution, caused by the surrounding steel mills, power plants, and severe traffic, is a big issue.

With the rapid economic development in the selected cities, the extensive use of fossil energy exerts tremendous pressure on the natural environment. Except for Guangzhou in Group 1 and Yangzhou in Group 2, the results for all cities meet the theoretical expectations for a long or short period. However, it is not the city with the worst air quality that fits the theoretical expectations best. Instead, the above-mentioned trends are more likely to be found in cities with a developed industry and bad air purification.

5.2. Country's results

[Figure 14](#) shows the results from the processing of the country data. [Figure 14](#) shows that, at 1–4 months frequency, oil prices are positively correlated to the PM2.5 concentrations from September 2013 to September 2014, March 2015 to June 2016, and August 2016 to August 2017, and the oil prices lead the PM2.5 concentrations. In the three groups of 12 cities, the results for most cities meet the theoretical expectations, as do the results from the country data. That is to say, the substitution effect caused by the rise of international oil prices tends to be greater than the macro effect, which eventually worsens China's air pollution.

Table 2. The data sources and their time span of x positively correlated with y , and x leading y .

Groups	Data sources	Time span (months)
Group 1	Ningbo	12
	Dalian	14
	Xiamen	5
	Guangzhou	1
Group 2	Qingdao	11
	Hohhot	16
	Shanghai	27
	Yangzhou	0
Group 3	Wuhan	7
	Jinan	11
	Harbin	7
	Beijing	4
	Country	34

Source: Authors' calculation.

6. Discussion and conclusions

6.1. Discussion

The results of the wavelet analysis indicate that, in general, there is a short-term positive correlation between international oil prices and PM2.5 concentrations, except for a few cities, where oil price fluctuations lead during a certain period. The results of the country data are even more consistent with this finding. The country data obtained by 74 Chinese cities is an appropriate representative of the entire country.

The effects of international oil price fluctuations on PM2.5 concentrations vary across cities. Table 2 shows the time span over which x leads y and they are positively correlated. From the table, we can see that the bad air quality is not very associated with a longer time span. In Group 2, the three cities (excluding Yangzhou) have a longer time span, especially Shanghai. The average, median, and sum of the time span in this group are higher than the others. These cities, Shanghai, Wuhan and Hohhot, are industrially developed, which keeps high rates of energy consumption. Among them, Wuhan still consumes a significant amount of fuel for its vigorous revival plan. Therefore, the energy utilisation of these cities tends to be greatly affected by changes of international oil prices, making the relationship between air pollution and oil prices more prominent.

The cities that maintain a short time span are classified into two categories. Xiamen, Guangzhou and Yangzhou belong to the first category. Xiamen and Guangzhou are located on the southeast coast. They both have strong monsoons and a large amount of precipitation, which contribute to the diffusion of airborne particles, resulting in good air quality throughout the year. Yangzhou, with an average annual rainfall of more than 1000 mm, maintains a comprehensive vegetation coverage. As a famous tourist city, the public has a strong sense of environmental protection, and the local government implements strict environmental protection policies. These three cities have fewer energy-consuming industries and no burden of winter heating. The relationship between energy demand and oil price fluctuations is not tight in these cities; with several factors that are beneficial to air quality (such as climate), the connection between x and y becomes negligible. The second category contains Beijing, Harbin and Jinan. In the most polluted group, Beijing and Harbin are

famous industrially developed cities in the north of China. The exhaust gas from the surrounding factories spreads to Beijing, which worsens the air pollution. Harbin is the northernmost provincial capital of China and has very large coal consumption for winter heating. Jinan is surrounded by mountains and has poor air self-purification ability. These are the main reasons for the poor air quality in the three cities. By contrast, the effects of international oil price fluctuations on the PM_{2.5} concentrations in these cities are not very prominent. Although the time spans in different cities vary due to the influence of geography, climate, economy and other factors, it still can be seen that in those areas with severe dependence on fossil energy, the international oil price fluctuations are more likely to affect the air quality.

Using the CGE model, Ma and Wei (2016) prove that, in the short run, air quality will be better when international oil prices rise. This conclusion is highly dependent on the assumption that there is a linear relationship between PM_{2.5} and SO₂ emissions. The increase in oil prices can certainly induce partial emission reduction. However, this is a little arbitrary and lacks consideration for substitution effects. Pollution caused by the consumption of other energies should be considered fully. As an emerging economy, China is still facing many difficulties in developing clean energy, in terms of both technology and capital. Peng-Hui and Liang (2015) reveal that the promotion of new energy is not feasible in a short period. High oil prices cannot impel the widespread use of clean energy quickly enough, but will intermediately increase more consumption of environmentally unfriendly alternatives, thus the substitution effects brought by high oil prices finally do harm to the air quality. In this study, we determine that the substitution effect caused by international oil price fluctuations is greater than the macro effect, regardless of whether the data of the 12 cities or country data are used.

In summary, the heavier the dependence on imported oil, the more effect the international oil price fluctuations exert on the atmospheric environment. To some extent, policies, geographical and economic factors can affect air quality a lot. But in general, for China, the substitution effect brought about by international oil price fluctuation is greater than the macro effect.

6.2. Conclusions

China lacks oil, and its rapid development has gradually increased its dependence on international oil. Under this circumstance, international oil prices are exerting a more and more significant influence on China's utilisation of fossil energy through the macro and substitution effects. However, China's demand for international oil is more affected by economic development other than oil prices. In the past few decades, China's economy has developed rapidly, and the demand for international oil has increased quickly too. As a result, oil demand is price inelastic in China and the rise in international oil prices hardly leads to a significant decrease on import and consumption of oil (Kun-Wang & Wei, 2008). Therefore, the macro effect tends to be weak.

On the other hand, when the price of oil increases substantially, cheaper alternatives are widely used, although they give rise more serious air pollution. This substitution is gradual and widespread. Since China's industry is built on coal, there is a relatively large substitution space between oil and coal, and the latter is much cheaper

owing to the abundant reserves and price restriction policy.⁴ Even though several technical obstacles exist in this kind of substitution, it is common that the inferior oils are used more in many industrial sectors and transportation. In total, when the oil prices rise the macro effect improves the air quality while the substitution effect does the reverse. According to the empirical results, international oil prices are positively correlated with PM2.5 concentrations, which indicates that the substitution effect is more effective than the macro effect when oil prices rise. A similar phenomenon could happen in other developing countries, especially those that have huge demands on imported energies.

This study shows that oil prices exert negative effects on air quality. Some important policy implications are available for government in this respect. In order to achieve a balance between economic development and environmental protection, the major priority is to maintain a cheap price for relatively environmentally friendly energies, including oil, natural gas, and so on, and switch towards clean systems (Sodeyfi & Katircioglu, 2016). Developing alternative sources of energy, especially renewable energy sources such as hydropower, should be encouraged by subsidies or incentives (Jumadilova, 2012). As a major energy demander, it is also necessary for China to build an energy-saving and environmentally friendly energy utilisation system. An increase in oil reserves, particularly commercial reserves, could reduce or minimise the adverse impact of oil markets. In addition, we propose the introduction of multi-channel funds, including overseas funds, to increase the international influence of China's crude oil futures and enable the full impact of the pricing power of crude oil futures. It is not only beneficial to stabilise the economy, but also does good to the environment.

Certainly, climate, vegetation coverage, environmental policies, and industrial structures could affect a city's air quality to some extent. In the empirical analysis, we mainly focus on oil price fluctuations, rather than on the uniqueness of each city. This study does not contain samples from Xinjiang, Tibet and Qinghai provinces in the west because of missing data. The 12 cities selected for the study are discretely distributed throughout the eastern and central parts of China, which contain more than 70% of the population and industry. In the future, in addition to including a detailed industrial structure, we shall specifically analyse the impact of oil price fluctuations on different industries and how this effect ultimately changes air quality. Furthermore, considering natural factors such as the climate, we can develop a better understanding of the phenomena in this study that do not meet theoretical expectations. Similar research can be replicated for other countries that have experienced rapid economic development and depend heavily on import energies for comparison purposes.

Notes

1. China has 34 provincial administrative regions including 23 provinces, 5 autonomous regions, 4 municipalities and 2 special administrative regions.
2. Monte Carlo simulations are based on 10,000 repetitions.
3. In the wavelet coherency diagrams, the semicircular areas provide reliable information without the edge effects, where red and blue colours correspond to strong and weak co-

movements between x and y , and the black lines here designate the 5% significant level. The phase difference parts distinguish positive or negative co-movements and lead–lag relationship between the variables. See more details in Section 4.2.

4. In China, the government strictly limits the price of coal owing to its great importance. Enterprises usually ensure constant coal price by long-term contracts.

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