IMPACT OF TRADE OPENNESS ON ENVIRONMENT IN CHINA

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Abstract. The study investigates the impact of trade openness on pollution in China by applying wavelet-coherence analysis, phase-difference technique and Breitung and Candelon (2006) causality test. The estimated results provide some dynamic association between trade openness and pollutant variables. The results indicate that trade openness has increased pollution in China especially after 2001 when China became member of WTO. It suggests that “pollution haven hypothesis” exists in China. These results imply that trade openness has increased exports which has increased domestic production by increasing the scale of industries, which in turn has increased pollution in the country. The findings of spectral domain causality test show that trade openness causes carbon emission both in short, medium and long runs. It indicates that trade openness forecast carbon emissions in China. The results suggest that China should take suitable measures while following trade openness policy to avoid pollution.

Keywords: China, pollution, trade openness, wavelet, phase-difference, causality.

JEL Classifications: F18, Q56.

Introduction

China initiated the process of trade reforms in 1978, which increased its volume of trade at a remarkable level. The share of trade in China's GDP which was 20.28% in 1982 shot up to 39.15% in 2000. After joining WTO in 2001, this share further increased to 63.96% in 2006. Today, China has the world's largest trading volume worth $4.1 trillion which has made China the largest exporter of goods in the world with $2.26 trillion of exports and second largest importer of goods with $1.84 trillion imports (World Bank, 2018). This trade liberalization policy along with other economic reforms helped China to enjoy high economic growth rate. Economic growth rate which was 5.17% in 1981 increased to 14.21 in 1992 and to 14.23 in 2007 (World Bank, 2018). It has increased the per capita income of the people from $197 in 1981 to $959 in 2000 and to $8123 in 2016. It has reduced the poverty level and has improved the living standards of the people.
This high trade has also affected the environment in China. Opponents argue that trade openness has deteriorated the environment as large scale production for exports has turned China into “world factory” and “manufacturing power house” which has increased the energy consumption and hence has increased the carbon emissions. The total value of international trade increased from $41 billion from 1982 to $4100 billion in 2017 and the total amount of carbon emissions increased from 1 580 260 (kt) to 10 998 324 (kt) during the same period. Therefore, it is claimed that high pollution in China is due to its free trade policies. The question arises whether trade openness has increased or decreased pollution in China.

Theoretically, trade openness has three effects on pollution i.e. scale effect, composition effect, and technology effect (Antweiler et al., 2001; Cole & Elliott, 2003; Copeland & Taylor, 2004; Farhani et al., 2014). Scale effect suggests that trade increases production, which will increase energy consumption. It will deteriorate environment by emitting carbon emissions. According to composition effect countries change production composition on the basis of their comparative advantage. If trade increases the demand for labor-intensive (capital-intensive) goods then pollution will decrease (increase) because production of labor-intensive (capital intensive) goods does not increase (increases) emissions. It is known as factor endowment hypothesis (FEH). Since developed countries are capital-intensive and less developed countries are labor-intensive, trade will increase pollution in developed countries and will decrease pollution in less developed countries. To attract foreign firms, less developed countries have lenient environmental standards. It will increase pollution in these countries. In literature this concept is called pollution haven hypothesis (PHH). The net effect of composition effect depends on whether FEH or PHH dominates. According to technique effect trade openness will spread environment friendly and energy efficient technology between countries which will decrease pollution. In less developed countries, both scale and composition effects may dominate the technique effect, thus trade may deteriorate environment. In turn, in developed countries technique effect will dominate both scale and composition effects, therefore, the net impact of trade is beneficial to environment.

Several studies have examined the impact of trade intensity on pollution both in China and other countries. Section 2 discusses review of literature in detail. The literature has provided the mixed and controversial effect of trade on pollution. Some studies have shown detrimental while others have shown beneficial effect of trade on pollution. These mixed and inconclusive results could be due to different assumptions, study objectives, econometric methods used, pollution variables, period of analysis, panel vs times series data, cross-sectional units taken, single vs multi-country analysis, etc. It calls for further analysis between trade and pollution in China as it is the largest pollution emitter country in the world and also has world’s largest trade volume. The importance of this study is that it uses wavelet technique to analyze trade-pollution linkages as the earlier studies have applied conventional econometric methods to examine the association between trade and pollution. The advantage of wavelet method is that it helps to find lead-lag association between variables across time and frequencies. Further, it helps to identify the interaction between variables in short, medium and long runs, which helps to formulate and implement the policies accordingly. Previously, Jun et al. (2018) have used such approach to analyze the impact of foreign direct investment (FDI) on pollution in China. This paper is extension of Jun et al. (2018) to analyze the impact of trade openness on pollution in China.
The study proceeds as follows. Next section provides trade openness and pollution patterns in China. Section 2 briefly describes empirical literature. Section 3 discusses the theoretical framework. Section 4 explains the estimated results. Final section provides the conclusion.

1. Trade pattern and environment condition in China

Since its reforms from a planned economy to an open economy in 1978, China has witnessed an impressive growth in trade in last thirty years. Figure 1 explains the pattern of exports, imports and total trade of China after economic reforms. The first few years after the reforms, there was no significant increase in trade as it was just $41 billion in 1982. Trade has risen dramatically since the beginning of 1990s, with 1992 having $165 billion trade volume, which continued throughout 1990s. After joining WTO in 2001, trade quadrupled and reached to $620.7 in 2002. During financial crisis of 2008 trade declined from $2563 billion in 2008 to $2207 billion in 2009, which recovered and continued to increase. Today, China has the world’s largest trading volume worth $4.1 trillion which has made China the largest exporter of goods in the world with $2260 billion of exports and second largest importer of goods with $1840 billion imports (World Bank, 2018).

![Figure 1. Exports, imports and total trade (Billion $) (source: World Bank, 2018)](image_url)

It is argued that high exports have turned China into world factory which has increased pollution in the country. China is the biggest carbon emitter globally in 2017, with 30% of global CO₂ emissions and it will remain on track to peak its carbon emissions by 2030. Annual average CO₂ emissions growth was more than 10% from 2000 to 2010 and was 3.22% in 2016 compared to 10.91% in 2011. Total carbon emissions have increased from 2 442 431(kt) in 1990 to 10 745 401 (kt) in 2016. Alternatively, carbon emissions have increased from 2.15 metric tons per capita in 1990 to 8.09 metric tons per capita in 2016. In 2014, CO₂ emissions per capita in China was 7.54 metric tons, far beyond the global average of 4.97 metric tons (World Bank, 2014). It shows that trade has increased pollution in the country.
2. Empirical literature

Empirically, several studies have investigated the effect of trade on environment in different countries. Some studies have found that trade openness improves environment as it reduces pollution (Kanjilal & Ghosh, 2013; Dogan & Turkekul, 2016; Antweiler et al., 2001; Boulatoff & Jenkins, 2010; Copeland & Taylor, 2003, 2004; Frankel & Rose, 2005; Birdsal & Wheeler, 1993; Ferrantino, 1997; Grether et al., 2010; Cole & Elliott, 2003; Erdogan, 2014; Cherniwchan, 2017). While some other studies have shown that trade has increased pollution and has vandalized the environment (Atici, 2012; Shahbaz et al., 2014; Al-Mulali & Sheau-Ting, 2014; Kellenberg, 2009; Kukla-Gryz, 2009; Managi & Kumar, 2009; Dean, 2002; Ang, 2009; Jalil & Feridun, 2011; Nasir & Rehman, 2011; Copeland & Taylor, 1994; Li et al., 2015; Feridun et al., 2006). According to Le et al. (2016) trade decreases pollution in high-income countries and increases pollution in middle and low income countries. Previously, Baek et al. (2009) have also shown that trade improves environment in developed countries and it deteriorates environment in less developed countries as former countries have strong environment regulations and latter countries have lax environmental regulations to attract foreign firms. Similarly, Managi et al. (2009) have shown that trade improves environment in OECD countries and deteriorates environment in non-OECD countries.

According to Chang (2015) trade openness increases carbon emissions in countries which have high corruption and decreases in countries which have low corruption. Previously, Copeland (2005) has also pointed out that trade improves environment but only in the presence of good governance. Damania et al. (2003) have also shown that the impact of trade openness on environment is contingent upon corruption level. Some studies have shown that trade and environment are not related as these studies have found insignificant effect of trade on environment (Farhani et al., 2014; Jalil & Mahmud, 2009; Jayanthakumaran et al., 2012). Recently, Sun et al. (2019) have shown that the effect of trade openness on pollution varies in different countries. Thus, empirical literature has given inconclusive effect of trade on environment.

Some empirical studies have also been conducted for China. Table 1 gives the summary of these studies. The table reveals that some studies have found the detrimental effect of trade openness on environment (He, 2009; Weber et al., 2008) while some studies have found that trade is beneficial for environment (Dean & Lovely, 2010). According to Shen (2008) trade openness has different effect on pollutant variables as trade openness increases air pollution while it decreases water pollution. Some studies have used input-output analysis and have shown that international trade has increased pollution in China (e.g. Wang & Watson, 2008; Weber et al., 2008; Lin & Sun, 2010; Xu et al., 2011; Yunfeng & Laike, 2010). Fang et al. (2018) have shown that trade openness decreases industrial wastewater emissions and increases sulfur dioxide emissions in China.

These studies have provided mixed and controversial conclusion because different studies have used different theoretical and econometric models, data types (time series vs panel), different panels of provinces or cities, different estimation techniques and different variables. All studies have explored the effect of trade on environment using control variables. Not a single study is available which has explored the sole effect of trade intensity on pollution. Further, no previous study has used wavelet technique for the analysis. This study will explore the
sole impact of trade on environment using the wavelet coherence approach as it will better highlight the effect of trade intensity on environment in China.

Table 1. Empirical literature – fact sheet

<table>
<thead>
<tr>
<th>Studies</th>
<th>Data Type(s)</th>
<th>Period of Analysis</th>
<th>Pollution Variable(s)</th>
<th>Econometric Technique</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shen (2008)</td>
<td>Panel data for 31 provinces</td>
<td>1993–2002</td>
<td>Sulfur dioxide (SO₂), dust, chemical oxygen demand (COD), arsenic, cadmium</td>
<td>Fixed and Random Effect Models</td>
<td>Trade openness has different effect on pollutant variables. Trade openness increases air pollution (SO₂ and dust fall) while it decreases water pollution (COD, arsenic and cadmium).</td>
</tr>
</tbody>
</table>
3. Theoretical framework

3.1. Wavelet analysis

Wavelet is a mathematical tool which describes data in various frequency components and then read each component according to its scale. It has advantage over Fourier method as it has both frequency and time resolutions while Fourier technique has only frequency resolution and no time resolution. The continuous wavelet transformation (CWT) of a time series \( x_n \ (n = 0, \ldots, N - 1) \) with uniform time step \( \delta t \) and scale (frequency) \( s \) is written as

\[
W^x_m(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \psi^* \left( (n - m) \frac{\delta t}{s} \right), \quad m = 0, 1, \ldots, N - 1.
\]  

(1)
Wavelet has different functional forms e.g. Haar, Mexican hat, Morlet, Daubechies, etc. Among these functional forms Morlet wavelet is an important wavelet to study synchronism among time series (Goupillaud et al., 1984). It is written as

\[ \psi_\eta(t) = \pi^{-\frac{1}{4}} \left( e^{i\eta t} - e^{-\frac{\eta^2}{2}} e^{-\frac{t^2}{2}} \right) \]  

(2)

where \( \psi(t) \) is Morlet wavelet function and \( \eta \) is non-dimensional “time” parameter. This wavelet function is analytic. The Fourier transformation of this function is supported in \((0, \infty)\). For \( \eta \geq 5 \) the term \( e^{-\frac{\eta^2}{2}} \) becomes negligible and the above function becomes

\[ \psi_\eta(t) = \pi^{-\frac{1}{4}} e^{i\eta t} e^{-\frac{t^2}{2}}. \]  

(3)

Now this function has some mass on \((-\infty, 0)\). The wavelet power spectrum can be calculated as \( |W_n\eta|^2 \), which measures variance at each time and scales.

### 3.2. Coherency and phase difference analysis

The wavelet coherency between two series in time frequency is expressed as

\[ R_n(s) = \frac{\phi(s^{-1} W_n^{xy}(s))}{\phi(s^{-1} |W_n^x|)^{1/2} \phi(s^{-1} |W_n^y|)^{1/2}}, \]  

(4)

where \( \phi \) is smoothed operator at time and scale. The phase difference \( \phi_{x,y} \) between \( x(t) \) and \( y(t) \) is given as (Aguiar-Conraria et al., 2008)

\[ \phi_{x,y} = \tan^{-1} \left( \frac{u(W_n^{xy})}{v(W_n^{xy})} \right), \]  

(5)

where \( u \) (or \( v \)) is real (imaginary) part of a complex number. Two series will fluctuate together when phase difference is zero at the identified frequency. The series are in phase (positively correlated) and \( y \) leads \( x \) when \( \phi_{x,y} \in \left[ 0, \frac{\pi}{2} \right] \), and \( x \) leads \( y \) when \( \phi_{x,y} \in \left[ -\frac{\pi}{2}, 0 \right] \), respectively. In turn, the series are in anti-phase or out of phase (negatively correlated), when the phase difference is \( \pi \) or \(-\pi\). If \( \phi_{x,y} \in \left[ -\pi, -\frac{\pi}{2} \right] \) then \( y \) is leading, and if \( \phi_{x,y} \in \left[ \frac{\pi}{2}, \pi \right] \) then \( x \) is leading.

### 3.3. Causality test

Wavelet-based causality measure of Olayeni (2016) is based on Rua (2013) wavelet correlation measure. Rua (2013) wavelet correlation measure is expressed as

\[ \rho_{xy}(s, \tau) = \frac{u(W_{xy}(s, \tau))}{\sqrt{|W_x(s, \tau)|^2 |W_y(s, \tau)|^2}}, \]  

(6)
\( \rho_{xy}(s, \tau) \) ranges between \(-1\) and \(1\) i.e. \(-1 < \rho_{xy}(\tau, s) < 1\). This correlation measure shows comovements at time and frequency simultaneously. The CWT-Granger causality test is written as

\[
G_{x \rightarrow y}(s, \tau) = \frac{u(W_{xy}(s, \tau))I_{x \rightarrow y}(s, \tau)}{\sqrt{|W_x(s, \tau)|^2 |W_y(s, \tau)|^2}},
\]

(7)

where \( I_{x \rightarrow y}(s, \tau) \) is an indicator function and is defined as

\[
I_{x \rightarrow y}(s, \tau) = \begin{cases} 
1, & \text{if } \phi_{xy}(s, \tau) \cap [0, \pi/2) \cup (-\pi, -\pi/2) \\
0, & \text{otherwise}.
\end{cases}
\]

(8)

4. Estimated results

4.1. Variable description and data source

The study has used two measures of trade openness i.e. total trade volume and total trade to GDP ratio to effectively capture its effect on pollution. Generally, trade to GDP ratio is used to measure trade openness (Squalli & Wilson, 2011). But this measure may fail to take into account trade openness intensity because it can increase, decrease or remain constant due to change in trade and GDP (Busse & Koeniger, 2015). Therefore, total trade volume is also used to capture trade openness intensity. Pollution is measured by carbon emissions. Two types of carbon emissions are taken i.e. volume of carbon emissions (kt), and per capita carbon emissions (metric tons). Data for trade intensity measures and CO\(_2\) variables is collected from the World Bank. Annual data is taken for the period 1982–2016, which is then converted into quarters.

4.2. Wavelet results

Wavelet technique is used to find the relationship between two non-stationary series. Thus, examining the stationary properties of the series is not required for the analysis (Aguiar-Conraria et al., 2008; Crowley & Mayes, 2009; Hallett & Richter, 2008; Boashash, 2015). For empirical analysis all variables are taken in their logarithm differences. Figure 2 plots the CWT power spectra of the trade and pollution variables, which basically show the power/variance of the variables. It is evident from this figure that trade has fluctuations between 2006 and 2012 at 1–4 quarters (high frequency\(^1\) or short term), and at 6–16 quarters (medium frequency or medium term to low frequency or long term). Thus, trade has high volatility at same period but at two different frequency levels. In fact, in this period trade increased in China after joining WTO in 2001. The same pattern holds for trade (% of GDP). CO\(_2\) variables have fluctuations at 1–6 quarters between 1995–2012. High fluctuation is also observed in long-run (from 32 quarters onwards).

\(^1\) The frequency bands are arbitrary.
Trade (current $)

Trade (% of GDP)

CO$_2$ emissions (kt)

CO$_2$ emissions per capita (metric tons)

Note: Thick black contour indicates 5% significance level (against the red noise). Color bar shows the color code for power that goes from low power (in blue) to high power (in red). X-axis shows the time period while the Y-axis shows the frequency (in quarters).

Figure 2. Wavelet power spectrum

4.3. Coherence and phase difference results

Wavelet coherency (WTC) plots are provided in Figure 3. These plots show that coherency vary across all frequencies at different times. Co-movements are observed between trade and CO$_2$ emissions (kt) at 8–20 quarters during 1982–1991, and 1997–2016, and at 30 above quarters during 1982–2014. The arrows being oriented up and right imply that trade causes CO$_2$ emissions positively. It suggests that trade increases CO$_2$ emissions. A similar pattern is found for trade and per capita CO$_2$ emissions. However, the red area has decreased in this case. The same findings are observed when trade (% of GDP) is used. However, the coherency differs across all frequencies at different time periods. Co-movements between two series are strong at relatively higher frequencies.
4.4. Causality and correlation results

Results of wavelet-based causality are provided in Figure 4. The color code moves from blue to red which indicates the degree of causal effects that goes from 0 to 1. In panel A, a strong causal effect is observed from trade to carbon emissions (kt) between 2007 and 2016 on 22~17 quarter scales. However, this causal effect has become little bit weak in case of per capita carbon emissions. The causality is found to be strong in case of trade (% of GDP) as shown in Panel B. To be brief, the causality results show that trade openness affects pollution variables in China.
Panel A: Causality from trade to emissions

Panel B: Causality from trade (% of GDP) to emissions

Per Capita CO\textsubscript{2} emissions (metric tons)

Note: White (red) contour shows statistical significance at 5% (10%) level (computed based on 1000 Markov bootstrapped series).

Figure 4. Wavelet based causality from trade (current $) and trade (% of GDP) to emissions

Rua (2013) measure of CWT correlation is provided in Figure 5. Correlation of trade with pollution variables is provided in panel A. These plots show positive correlation among variables and this correlation is strong compared to the causal relationship as shown in Figure 4. The first plot indicates high positive co-movements between trade and CO\textsubscript{2} emissions (kt) during 2005–2016 at 10–18 quarters (low frequency bands). This positive co-movement is also persistent at low frequency for whole period. A similar positive correlation is found between trade and per capita emission. Same correlation is found between trade (% of GDP) and pollution variables (panel B). It again suggests that trade has deteriorated environment in China.
Panel A: Correlation between trade and emissions

Panel B: Correlation between trade (% of GDP) and emissions

\[
\begin{align*}
\text{CO}_2 \text{ emissions (kt)} & \\
\text{Per Capita CO}_2 \text{ emissions (metric tons)} & \\
\end{align*}
\]

**Note:** Blue (red) color shows negative (positive) correlations.

Figure 5. Wavelet based correlations (Rua, 2013)

### 4.5. Frequency-domain causality test

The conventional Granger causality test cannot detect causality in different time-scale, therefore, Breitung and Candelon (2006) causality test is used to find the causality among variables. This test examines causality between variables over different time scales i.e. short, medium and long run causality. According to this test the link between two series \( N \) and \( M \) in a stationary VAR model can be expressed as

\[
\begin{align*}
M_t & = \sum_{i=1}^{p} \rho_i M_{t-i} + \sum_{i=1}^{p} \psi_i N_{t-i} + \epsilon_t, \\
N_t & = \sum_{i=1}^{p} \lambda_i N_{t-i} + \sum_{i=1}^{p} \chi_i M_{t-i} + \nu_t.
\end{align*}
\]
The null hypothesis that $N$ does not cause $M$ in the frequency interval $\omega \in (0,\pi)$, is tested using $F$-statistics with the distribution $F(2, T - 2p)$. The results from spectral-domain causality test are provided Figure 6. The findings in panel A indicate that trade causes CO$_2$ both at short and long horizons as the values of test statistics exceed the critical values at 5% level of significance. The same holds for per capita CO$_2$ emissions. It indicates that trade predicts pollution in China. Causality is also found when trade (% of GDP) is taken.

Panel A: Trade ($Billions$)  
Panel B: Trade (% of GDP)  

Per Capita CO$_2$ emissions (metric tons)

Note: X-axis shows frequencies (omega) and y-axis shows the F-statistics. The horizontal red line shows 5% critical values.

Figure 6. Wavelet-based causality test

Conclusions

The paper investigates the impact of trade openness on pollution in China. The analysis is done by applying wavelet technique using data for 1982–2016 time period. The findings show that trade openness has increased pollution in China especially after 2001 when China joined WTO. It shows that “pollution haven hypothesis” exists in China. These results imply that trade openness has increased exports which has increased domestic production by increasing the scale of industries, which, in turn, has increased pollution in China. Causality results show that trade openness causes carbon emissions in short, medium and long runs. It reveals that trade openness forecast carbon emissions in China.

The study has some policy implications. China needs be careful about its trade openness policies to avoid pollution. The government should tighten the environmental regulations to
prevent pollution. Chinese exports are also driven by foreign companies; these strict rules will prevent these firms from investing in polluting industries, which will improve environment. Moreover, government needs to encourage R&D investment as it will improve the technical efficiency of local firms, which will help to decrease pollution in the country. These policy implications can be generalized to other developing and emerging economies to avoid pollution. These countries should take appropriate steps to avoid pollution before opening their borders for trade. The main limitation of the study is that it has considered only single determinant of pollution which is trade. Future research can be extended by taking into account some other variables like income, energy consumption, etc.

**Author contributions**

All authors carried out empirical analysis and wrote the draft of the paper. Hamid Mahmood collected data and designed the model. Wen Jun was responsible for supervising the analysis and editing the work. Muhammad Zakaria done the supportive work and critically analyzed the work.

**Disclosure statement**

Authors do not have any competing financial, professional, or personal conflict of interests from other parties.

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