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Sectoral CO_2 emissions in China: asymmetric and time-varying analysis

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Today, China is the second-largest, fastest-growing economy in the world. This study analyzes asymmetric and time-varying impact of world energy prices (including world energy prices index, world coal prices, world crude oil prices and world natural gas prices) on China's CO_2 emissions. We used a non-linear ARDL (NARDL) model and wavelet analysis using monthly data from 1992 to 2017. The results based on the NARDL estimate show that world energy prices have an asymmetric impact on CO_2 emissions. However, the results of wavelet pairwise correlation and wavelet-transform coherence suggest that the relationship between world energy prices and CO_2 emissions differs over time and across sectors (i.e. short-term, medium-term, long-term and very long-term). Evidence suggests that ignoring fundamental non-linearities can lead to misleading outcomes. Such empirical results are expected to have a high importance for the efficient design and implementation of world energy prices and Chinese environmental policies.

Keywords: carbon emissions; world energy prices; NARDL; wavelet; China

1. Introduction

China's growth as an economic force has become a key factor for regional and global energy use and environmental impacts. Being the world's largest CO_2 emitter, China's carbon emissions received considerable scrutiny from national and foreign scientists (Liu *et al*. 2015; Fatima *et al*. 2019; Wang and Jiang 2019). Climate change has been driving CO_2 emissions from human activities (Masood, Farooq, and Saeed 2015). These emissions are primarily from China, which has had the world's largest carbon footprint since 2004, accounting for 28.5% of global CO_2 emissions in 2018. The country has become the third-largest oil consumer with the sixth-largest proven oil reserves. Compared to the scale and composition of energy use, China accounts for more than 29% of global CO_2 emissions, while fossil fuel consumption is 13%. Due to the steady growth in Chinese transportation and industry, energy demand is increasing. While the share of other primary sectors including commercial and public sectors in China's energy demand is 15% and 4%, respectively. Owing to the ongoing industrialization cycle, environmental and energy policies have significant impacts on global CO_2 emissions. The Chinese economy's scale also represents energy demand in the country (Fatima, Xia, and Ahad 2018, 2019; Fatima *et al*. 2018a, 2018b, 2019).

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China's demand for energy is increasing more rapidly than any other nation in the world. The rise in world energy pricing is mainly motivated by the increase in supply, and China plays an important role in global energy prices and CO_2 emissions. Regardless of the rapid growth of the energy sector, China is the world's biggest CO_2 emitter (Bilgili, Mugaloglu, and Koçak 2018). A study by Wang and Su (2020) reported that CO_2 emissions in developed countries (China) increased faster than in emerging countries. Chinese new work explored the relationship between energy usage and carbon dioxide with linear econometric models. However, energy prices affect China's CO_2 emissions tremendously.

Also, the relationship between energy prices and CO_2 emissions was established based solely on domestic energy prices in China (see Hammoudeh *et al*. 2015; Li, Fang, and He 2019; Wang, Bai, and Xie 2019; Cheng *et al*. 2019). Any country's economic growth depends on energy (Wang, Bai, and Xie 2019) and a study coordinated by Chai, Lu *et al*. (2016) found that world energy prices directly affect China's environmental quality through Chinese manufacturing, transport and economic development. Interactions between world energy prices and the Chinese energy consumption trend should be more important than ever (Cong *et al*. 2008). Research by Long and Liang (2018) found that shocks in global energy prices have direct effects on production costs in any economy and significant effects due to changing the development environment (CO_2). Before 1980, the local government established Chinese oil and petroleum retail and wholesale prices, although, in 1998, China's oil prices were strongly correlated with world oil prices.

Due to China's strong correlation with global energy prices, this study examines the relationship between world energy and China's CO_2 emissions. This study contributes to energy–CO_2 literature in various ways. First, we examine the relationship between world energy prices (including the world energy price index, coal, crude oil and gas prices) and China's CO_2 emissions (overall CO_2 emissions, manufacturing and transport sector emissions). Initially, we analyze the individually asymmetric effect on CO_2 emissions of energy prices and then combine it using a non-linear ARDL method. Therefore, this research also has strategic consequences for some of China's most influential industries.

Second, the problem of asymmetries or non-linearities attracts attention from all over the world due to the intricacy of economic systems regulating the mechanism of data generation in energy prices and CO_2 emission markets. Moreover, global financial crises, new rules and regulations, and sudden policy changes create non-linearities among data series. Examining the linear relationship between energy prices and CO_2 emissions may be misleading. Considering the importance of non-linearities, this study used the non-linear ARDL approach introduced by Shin, Yu, and Greenwood-Nimmo (2014), which accommodates non-linearities among sequences, sudden splits and volatility, and provides robust results in a non-linear system (Meo *et al.* 2018a). Using the non-linear ARDL model, we can distinguish how CO_2 emissions respond to positive and negative changes in world energy prices. Third, conventional econometrics methods look only at time – but neglect the most relevant frequency domain information such as short-, medium-, long- and very long-run (Power and Turvey 2010). Several researchers found that time series non-linearity occurs due to information that is hidden in the frequency field (Huang *et al*. 2015). To analyze time and frequency domain information at the energy price and CO_2 nexus, wavelet-based analysis is a great method, as energy prices and CO_2 emissions exhibit time-varying relationships.

Wavelet-based analysis works well in structural splits, unlike many other econometric techniques. Wavelet analysis operates by decomposing time data into a two-dimensional time-frequency sphere and can define the effect of regime changes and analyze the short-run and long-run dynamics between energy price and CO_2 emissions. Hence, our research uses both non-linear-ARDL (NARDL) by Shin, Yu, and Greenwood-Nimmo (2014) and a wavelet response approach to find: (1) is there any asymmetric relationship between energy price and CO_2 and to what extent? And (2) with time and frequency information, is there a lead–lag relationship between energy price and CO_2 and if so, how long is the lead/lag.

The study is structured as follows: Section 2 addresses the literature review. Section 3 addresses the research data and methodology. Section 4 addresses the outcomes. Section 5 provides conclusions and policy implications.

2. Literature review

2.1. CO_2 emissions and energy prices

The previous literature analyzed many determinants of CO_2 emissions, including economic development, FDI inflows, human health, energy use, energy supply, urbanization, globalization and energy prices (Fei *et al*. 2011; Bai and Yang 2012; Chang 2010; Feng, Sun, and Zhang 2009; Zhang and Yang 2013; Li, Li, and Lu 2017; Fatima, Xia, and Ahad 2018; Alvarado *et al*. 2018; Azam, Khan, and Ozturk 2019; Khan, Teng, and Khan 2019a, 2019b).

A review by Maji *et al*. (2017) showed that researchers focused on energy use and CO_2 emissions, ignoring the relationship between energy prices and CO_2 emissions. While some studies found contradictory results in the correlation between energy prices and CO_2 emissions.

For example, Yang and Timmermans (2012), Payne (2012), Wang, Li, and Fang (2018), Zhang and Zhang (2016), Winchester and Ledvina (2017), Maji *et al*. (2017) showed that the rising price of oil has a negative impact on CO_2 emissions. Although few studies by Chai, Lu, *et al*. (2016), Nwani (2017) and Blazquez *et al*. (2017) found that increasing energy prices lead to higher carbon dioxide emissions. This doesn't mean rising energy prices increased China's CO_2 emissions. We also found another line of CO_2 modeling literature (Salim and Rafiq 2012) and Blazquez *et al*. (2017) found no important association between oil prices and CO_2 emissions.

Subsequent energy demand channelizes the effect of oil prices on CO_2 emissions (Amano 1990; Martinsen, Krey, and Markewitz 2007; Fei and Rasiah 2014). Research by Zhang, Broadstock, *et al*. (2014) analyzed the effect of energy prices on energy demand in different sectors and found that higher prices influence most transport sectors. Zafeiriou *et al.* (2014) argued that when energy costs increase, consumers see an alternative to conventional energy supplies, and as traditional energy sources decline, CO_2 emissions slowly decrease. Owing to higher oil prices, energy demand also depends on coal use, sector and other factors. Sun *et al*. (2018) explained that some pulp and paper industries consume the largest resources and are the source of pollutant emitters in the manufacturing sector (Table 1).

Li *et al*. (2018) discussed how the non-ferrous metal industry (NMI) absorbs vast quantities of energy and is a catalyst for China's high-carbon industry. Table 2 also summarizes a few studies illustrating the relationship between CO_2 and energy prices.

Table 1. Summary of the empirical literature on the determinants of CO_2 emissions in China.

Authors	Country	Method	Dependent variables	Determinants
Jalil, Feridun, and Ma (2010)	China	ARDL	CO_2	Financial development, economic growth, energy consumption
Chang (2010)	China	Multivariate cointegration, VECM	CO_2	Energy consumption, growth
Bai and Yang (2012)	China	Panel OLS, cointegration	CO_2	Energy consumption, GDP
Zhang, Broadstock, and Cao (2014)	China	ARDL	CO_2	Economic growth, industrial structure, urbanization
Wang *et al.* (2014)	China	Panel cointegration	CO_2	Energy consumption, GDP
Zhang (2011)	China	cointegration theory, Granger causality test, variance decomposition	CO_2	Financial development
Wang *et al.* (2014)	China	Panel data model	CO_2	Per capita energy consumption, urbanization
Long *et al.* (2015)	China	Cointegration test, impulse response, Granger causality	CO_2	Energy consumption, economic growth
He *et al.* (2017)	China	STIRPAT model	CO_2	Urbanization, urbanization, GDP, GDP 2, technology level
Awan *et al.* (2018)	Pakistan	ARDL	CO_2	GDP, FDI, Trade
Wang and Zhang (2020)	BRICS	FMOLS	CO_2	R&D, PGDP, energy structure, urbanization
Wang *et al.* (2016)	China	Cointegration test, impulse response, VECM	CO_2	Energy consumption GDP

2.2. Non-linear relationship of CO_2 emissions and other determinants

Several researchers have therefore studied non-linear CO_2 emission behavior in various countries, including Hammoudeh *et al*. (2015) for the USA, Zaghdoudi (2018), Ahmad *et al*. (2018), AhAtil *et al*. (2019) for China, Rahman and Ahmad (2019) for Pakistan and Haug and Ucal (2019) for Turkey. These studies have confirmed the asymmetric response of CO_2 emissions due to positive and negative changes in macroeconomic factors. After careful study of CO_2 emissions literature, we found that most research used standard time series and panel data approaches including VECM threshold, ARDL bound testing cointegration, Granger causality, VECM, Bootstrapped causality tests, FMOLS model, DOLS model, Multivariate conditional volatility model, Engle and Granger method, two-way random effect model, gravity model etc. All these techniques function effectively within a linear system, although most series have a non-linear relationship. Research by Po and Huang (2008) found that linear models do not tolerate or consider short-term fluctuations and effect systemic breaks. Similarly, Anoruo (2011) found that macroeconomic variables have non-linear properties, but linear models do not comply with them. Kahneman and Tversky (1979) expressed earlier the value of non-linearity, arguing that non-linearity is normal for human behavior.

Furthermore, Bildirici and Turkmen (2015) argued that non-linear econometric models are more predictive than linear models. CO_2 emissions were found to react differently to positive and negative energy price changes. During cycles of rapid economic growth, CO_2 emissions typically remain high, while CO_2 emissions are comparatively small during times of economic recession or low renewable energy prices.

However, financial crises, sudden policy shifts, domestic conflicts and financial system dynamics produce regime-switching actions of energy prices. This can contribute to energy and CO_2 emission non-linearities. Furthermore, new pricing strategies, technical progress and regulatory changes often contribute to asymmetries between energy prices and CO_2 emissions (Hammoudeh *et al*. 2015).

Considering non-linearities between energy prices and CO_2 emissions, therefore, is an important problem. From the literature, we find different gaps, first of all, earlier studies mostly examined the effect of energy consumption on CO_2 emissions; other researchers also examined the relationship between energy prices and CO_2 emissions, but considered only domestic energy prices. Second, earlier studies ignored the asymmetric correlation between world energy prices and China's CO_2 emissions, given China's various major sectors.

Third, the relationship between energy prices and CO_2 emissions changes over time, but researchers ignored this correlation. Therefore, we considered the asymmetric effect of world energy prices on China's CO_2 emissions in various sectors. For the non-linear relationship, we used the NARDL model. To examine the time-varying relationship we used wavelet-based analysis. Time series contains information not only in time, but also frequency domains. In addition to frequency analysis, time series in the time and frequency domains are considered by wavelet methods. The wavelet analysis examines the patterns, trends or seasonality produced by the transformation of time series over time. Wavelet models are far similar to time series and data panel models. Thus, wavelet analysis will inspect structural data breaks over time and frequency through transformation and permanent cycles to estimate dependence between two variables (Nie *et al*. 2019).

Table 2. Summary of literature on oil price and CO_2 emissions.

Authors	Country	Period	Method	Variables	Results
Payne (2012)	USA	1949–2009	Toda-Yamamoto causality	Renewable energy, Oil price, GDP	Increase (oil price) will decrease CO_2
Lim, Lim, and Yoo (2014)	Philippine	1965–2012	Cointegration and Granger causality	Oil consumption, CO_2, economic growth	Bidirectional causality between oil and CO_2
Salim and Rafiq (2012)	Brazil, China, India, Indonesia, the Philippines, and Turkey	1980–2006	FMOLS, DOLS, Granger causality	Real GDP, renewable energy, carbon emission, and real oil price	The oil price has no significant impact on CO_2 and renewable energy
Maji *et al.* (2017)	Malaysia	1983–2014	ARDL	CO_2, Oil price	Lower oil increase CO_2
Winchester and Ledvina (2017)	16 regions	2015–2050	EPPA model	Future oil price, biofuels, energy production, CO_2 emissions,	Increase oil price will increase biofuel and decrease CO_2 emissions
Yang and Timmermans (2012)	European Union (EU)	2004–2009	pseudo-panel approach	fuel prices and emissions	Increase fuel price reduce fuel consumption and CO_2 emissions
Chai, Zhou *et al.* (2016)	China	1987–2014	influence path analysis	International fuel price, energy consumption, CO_2 emission	Increase world fuel price increase CO_2 emission. increase energy consumption increase CO_2
Nwani (2017)	Ecuador	1971–2013	ARDL	Crude oil price, CO_2 emissions, energy consumption	Increase crude oil price increase energy consumption and CO_2 emissions
Blazquez *et al.* (2017)	Spain	1969 to 2003	(DSGE) model	Oil price and CO_2 emissions	fossil fuel prices have a significant impact on economic activity

Table 3. Functional forms of all models.

$CO_2 = f$ (WEP)	M 1.1 to 1. 4	CO_2t $= f$ (WEP)	M 3.1. to 3.4
$CO_2 = f$ (oil)		CO_2t $= f$ (oil)	
$CO_2 = f$ (coal)		CO_2t $= f$ (coal)	
$CO_2 = f$ (NG)		CO_2t $= f$ (NG)	
CO_2i $= f$ (WEP)	M 2.1 to 2.4	$CO_2 = f$ (WEP, oil, coal, NG)	M 4
CO_2i $= f$ (oil)		CO_2i $= f$ (WEP, oil, coal, NG)	M 5
CO_2i $= f$ (coal)		CO_2t $= f$ (WEP, oil, coal, NG)	M 6
CO_2i $= f$ (NG)			

Note: M refers to the model number. CO_2 refers to overall CO_2 emissions. CO_2i refers to CO_2 emissions from the industrial sector. CO_2t refers to CO_2 emissions from the transport sector. M 1.1 to 1.4, M 2.1 to 2.4, M 3.1 to 3.4, M4, M5, and M6 refers to the individual impact of world energy prices on overall CO_2 emissions, CO_2 emissions from the industrial sector, CO_2 emissions from the transport sector, combined effect of world energy prices on overall CO_2 emissions, CO_2 emissions from the industrial sector and CO2 emissions from the transport sector, respectively.

3. Data and methodology

This study analyzed the asymmetric/non-linear impact of world energy prices on China's environmental degradation. The world energy price includes world energy prices index, world crude oil, coal and natural gas prices. Also, this research analyzed the individual effects on China's environmental deterioration of world crude oil, coal and natural gas prices. We have used a range of environmental pollution indicators, such as CO_2 emissions from the transportation industry and the manufacturing sector, to monitor the robustness of the model. Consequently, the following are functional forms of bivariate and multivariate primary models.

In Table 3, CO_2, WEP, oil, coal, NG, CO_2i and CO_2t denote overall CO_2 emissions per capita, world energy prices index, world crude oil prices, world coal prices, world natural gas prices, CO_2 emissions from China's manufacturing industry sector and CO_2 emissions from China's transport sector, respectively. This study uses monthly data ranging from 1992 to 2017; world energy prices is an index; coal is the price of coal per ton; crude oil is the crude oil price per barrel; natural gas refers to the price of natural gas per MMBTU; CO_2 emissions as per capita (CO_2), CO_2 emissions from China's transport as a percentage of total fuel combustion and CO_2 emissions from China's manufacturing industries, also measured as a percentage of total fuel combustion; all the data was downloaded from the Thomson Reuters Data Stream. To examine the long-run relationship between the proposed variables, we used the following long-run equation

$$y_t = \beta_0 + \beta_1(x_t) + \mu_t \tag{1}$$

where y_t refers to dependent variables (CO_2, CO_2i and CO_2t) while x_t denotes exogenous variables (WEP, coal, oil and NG). After a careful review of literature on environmental studies, we found that most of the studies used linear econometric models (Li and Yang 2016; Ozturk and Acaravci 2016; Al-Mulali and Ozturk 2016; Ahmad and Du 2017; Alshehry and Belloumi 2017), while linear econometric models force variables to be linear even when the variables are not linear in reality.

3.1. NARDL method

Conversely, there are a few recent studies that confirmed the non-linear/asymmetric relationship between energy prices and CO_2 emissions (Hammoudeh *et al.* 2015;

Boufateh 2019). Given the importance of non-linearities, the current research employs a non-linear ARDL method, which explores short-term fluctuations and sudden variations in the proposed variables and offers short-term and long-term non-linear interaction between them (Meo *et al*. 2018b). The non-linear ARDL model is an extension of the traditional time series ARDL approach that produces short-run and long-run relationships (Khan, Teng, and Khan 2019; Fareed *et al*. 2018). Compared to any other cointegration-based approach, an important benefit of the NARDL model is that it can relax stationary constraints and be employed when the variables are $I(0)$ or $I(1)$ and $I(0)$ or $I(1)$ (Rasheed *et al*. 2019; Chang *et al*. 2019). The general form of the ARDL method we have used is, therefore:

$$\Delta A_t = \delta_0 + \delta_1 A_{t-1} + \delta_2 B_{t-1} + \sum_{i=1}^{k} \delta_3 \Delta A_{t-1} + \sum_{i=1}^{k} \delta_4 \Delta B_{t-1} + \varepsilon_t \tag{2}$$

In the above equation, we have: Δ difference operator, δ_1 and δ_2 as long-run and δ_3 and δ_4 short-run parameters, while A_t refers to dependent variables (CO_2, CO_2i and CO_2t) and B_t denotes exogenous variables (WEP, coal, oil, NG). The optimal lags are represented using AIC criteria with k. The run association between proposed variables is examined as the absence of cointegration $\delta_1 = \delta_2 = 0$. Apart from conventional cointegration and traditional cointegration, Granger and Yoon (2002) formed a new concept of "Hidden Cointegration." They argued that from the positive and negative components of a series, cointegration can also be found. For hidden cointegration, Schorderet (2003) endorsed an asymmetric regression model, but that only accommodates a single component of a series for the cointegration.

However, from the foundation-based research, Shin, Yu, and Greenwood-Nimmo (2014) formulated a non-linear autoregressive distributed lag model (NARDL) which decomposed a series into its positive and negative changes and provides non-linear relationships among the proposed variables. Asymmetric cointegration can be formulated as follows:

$$A_t = \delta^+ B_t^+ + \delta^- B_t^- + \mu_t \tag{3}$$

In Equation (3) A denotes endogenous variables, δ^+ and δ^- are long-run coefficients and B_t^+ and B_t^- are exogenous variables decomposed into positive and negative shocks as follows:

$$B_t = B_0 + B_t^+ + B_t^- \tag{4}$$

B_t^+ and B_t^- are the decomposed negative and positive components of an exogenous variable and the equations (Equations (5)–(12)) are the partial sums of positive and negative changes in WEP, oil, coal and NG, respectively

$$\mathrm{WEP}^+ = \sum_{i=1}^{t} \Delta \mathrm{WEP}_i^+ = \sum_{i=1}^{t} \max(\Delta \mathrm{WEP}_i, 0) \tag{5}$$

$$\mathrm{WEP}^- = \sum_{i=1}^{t} \Delta \mathrm{WEP}_i^- = \sum_{i=1}^{t} \min(\Delta \mathrm{WEP}_i, 0) \tag{6}$$

$$\mathrm{oil}^+ = \sum_{i=1}^{t} \Delta \mathrm{oil}_i^+ = \sum_{i=1}^{t} \max(\Delta \mathrm{oil}_i, 0) \tag{7}$$

$$\text{oil}^{-} = \sum_{i=1}^{t} \Delta \text{oil}_i^{-} = \sum_{i=1}^{t} \min(\Delta \text{oil}_{i,} 0) \tag{8}$$

$$\text{coal}^{+} = \sum_{i=1}^{t} \Delta \text{coal}_i^{+} = \sum_{i=1}^{t} \max(\Delta \text{coal}_{i,} 0) \tag{9}$$

$$\text{coal}^{-} = \sum_{i=1}^{t} \Delta \text{coal}_i^{-} = \sum_{i=1}^{t} \min(\Delta \text{coal}_{i,} 0) \tag{10}$$

$$\text{NG}^{+} = \sum_{i=1}^{t} \Delta \text{NG}_i^{+} = \sum_{i=1}^{t} \max(\Delta \text{NG}_{i,} 0) \tag{11}$$

$$\text{NG}^{-} = \sum_{i=1}^{t} \Delta \text{NG}_i^{-} = \sum_{i=1}^{t} \min(\Delta \text{NG}_{i,} 0) \tag{12}$$

As the NARDL cointegrating approach is an extension of the traditional ARDL cointegration model, it is demonstrated that if the positive and negative components of exogenous variables (from Equations (5)–(12)) are put into the linear ARDL framework shown in Equation (2), then the traditional ARDL approach can be converted into the non-linear/asymmetric ARDL framework

$$\Delta A_t = \delta_0 + \delta_1 A_{t-1} + \delta_2 B_{t-1}^{+} + \delta_3 B_{t-1}^{-} + \sum_{i=1}^{k} \delta_4 \Delta A_{t-1} + \sum_{k=1}^{k} \delta_5 \Delta B_{t-k}^{+} + \sum_{k=1}^{k} \delta_6 \Delta B_{t-k}^{-} + \varepsilon_t \tag{13}$$

3.2. The continuous wavelet transforms

The present study also employed wavelet-based analysis, including wavelet decomposition based on discrete wavelet transform (DWT), wavelet correlation and continuous wavelet transform (CWT). First, we employed wavelet decomposition based on DWT; with the help of wavelet decomposition analysis, one can easily decompose any variable into different periods such as short-term indicated by ($D_1 + D_2$), medium-run indicated by ($D_3 + D_4$), the long-run period indicated by ($D_5 + D_6$) and very long-run indicated by S_6. The wavelet decomposition analysis helps in variation checking within the series in different periods. Meanwhile, wavelet correlation analysis helps in determining the correlation between two series over the different periods, such as short-run, medium-run, long-run and very long-run. The prime objective of using CWT is to examine the lead–lag relationship between the world energy price index (and other forms of energy) and CO_2 emissions from China, as policymakers must devise policies related to energy prices and CO_2 emissions for the short-run, medium-run, long-run and very long-run. It is the beauty of CWT analysis that decomposes the relationship between proposed variables into different time frequencies and thus depicts the true co-movement among the proposed variables.

The continuous wavelet transform $w_x(u,s)$ is obtained by projecting a mother wavelet Ψ onto the examined time series $x(t) \in l^2\ (R)$, that is

$$w_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi \left(\frac{t-u}{s} \right) dt \tag{14}$$

here u refers to the time domain and s refers to its position in the frequency domain. Therefore, the wavelet transforms by mapping the original series into a function of u

Table 4. Descriptive statistics.

	CO_2	CO_2i	CO_2t	WEP	Coal	Oil	NG
Mean	4.645	32.442	7.335	91.810	58.954	61.491	3.973
Median	4.144	32.722	7.627	72.030	48.320	47.200	3.330
Maximum	7.577	37.318	9.203	249.610	195.190	167.700	13.630
Minimum	2.250	27.237	4.646	22.090	24.000	13.200	1.180
Std. Dev.	2.014	2.263	1.283	59.959	33.558	41.562	2.254
Skewness	0.332	–0.378	–0.623	0.713	1.177	0.722	1.501
Kurtosis	1.449	2.778	2.052	2.186	3.967	2.186	5.649
Jarque-Bera	36.173	7.912	31.197	34.289	82.417	34.973	203.848
Probability	0.000	0.0191	0.000	0.000	0.000	0.000	0.000

and s, which gives us information simultaneously on time and frequency. For finding the interaction between two-time series (e.g. how closely X and Y are interrelated by linear transformation), this study applied a bivariate framework called wavelet coherence. Following Torrence and Webster (1999), the wavelet coherence of two-time series can be defined as follows:

$$R_n^2(s) = \frac{\mathrm{IS}(\mathrm{s}^{-1}W_n^{xy}(s))\mathrm{I}^2}{S\left(s^{-1}\mathrm{I}W_n^x(s)\right)\mathrm{I}^2.S(s^{-1}\mathrm{I}W_n^y(s))\mathrm{I}^2} \tag{15}$$

where S is a smoothing operator, s is a wavelet scale, $W_n^x(s)$ is the continuous transformation of the time series X, $W_n^y(s)$ is the continuous wavelet transform of the time series Y, $W_n^{xy}(s)$ is a cross wavelet transform of the two-time series X and Y.

4. Empirical results

In this study, we implement an alternative econometric framework to determine the long-lasting and short-term asymmetrical impact on China's CO_2 emissions of world energy prices (including the price index for the world, coal, crude oil and natural gas), namely the non-linear autoregression model NARDL, recently advanced by Shin, Yu, and Greenwood-Nimmo (2014).

Before estimating the relationship between world energy prices and CO_2 emissions, the order of integration of the time series variables must be estimated, because it is an ARDL model's key weakness that the ARDL method cannot be implemented where there are any series stationary to $I(2)$.

The well-known Augmented Dickey–Fuller (ADF) and Phillip–Perron (PP) unit-root tests are used. The results of the descriptive statistics are given in (Table 4) while the unit root test results given in (Table 5) indicate that none of the variables is stationary on $I(2)$. It makes a model of non-linear autoregressive distributed lag (NARDL). F-test values for both models (M 1.4, 2.4, 3.4, 4, 5 and 6) presented in Table 6 are greater than the critical value of upper-bound, which confirms long-term relationships between the purposed variables (Pesaran, Shin, and Smith 2001). Next, we calculated short- and long-term asymmetric coefficients for all models (M 1.1 to 1.4, 2.1 to 2.4, 3.1 to 3.4, 4, 5 and 6) by decomposing world energy prices into positive and negative shocks. The NARDL strategy has the advantage that long-term asymmetric CO_2 emission responses are discriminated against due to positive and negative changes in world energy prices. For Models 1.1 to 1.4, the dynamic estimate and

Table 5. Unit root tests.

	Level		1st Difference		
Variable	ADF	PP	ADF	PP	Order of integration
CO_2	–1.1467	–0.198	–4.22**	–4.21**	I(1)
CO_2i	–4.38***	–4.725***	–2.99	–4.72	I(0)
CO_2t	–3.01	–2.37	–2.182***	–5.12***	I(1)
WEP	–1.376	–1.484	–4.68***	–4.67***	I(1)
Coal	–1.74	–1.598	–6.49***	–6.86***	I(1)
Oil	–1.36	–1.36	–4.55***	–4.54***	I(1)
NG	–1.89	–1.75	–6.62***	–6.82***	I(1)

Note: ***,** indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 6. Non-linear cointegration based on bounds testing approach.

Bivariate analysis	*F*-test	LB	UB
Model 1.1 to 1. 4 overall CO_2 emissions			
$CO_2 = f$ (WEP)	13.68*	4.87	5.86
$CO_2 = f$ (coal)	7.67**	4.19	5.06
$CO_2 = f$ (oil)	6.100**	4.87	5.85
$CO_2 = f$ (NG)	10.38*	4.19	5.06
Model 2.1 to 2.4 CO_2 emissions from the industrial sector			
$CO_2 = f$ (WEP)	6.95**	4.19	5.06
$CO_2 = f$ (coal)	10.91*	4.87	5.87
$CO_2 = f$ (oil)	6.44**	4.19	5.06
$CO_2 = f$ (NG)	6.19**	4.87	5.87
Model 3.1 to 3.4 CO_2 emissions from the transport sector			
$CO_2 = f$ (WEP)	6.79**	4.19	5.06
$CO_2 = f$ (coal)	14.65*	4.87	5.87
$CO_2 = f$ (oil)	6.71**	4.19	5.06
$CO_2 = f$ (NG)	6.51**	4.19	5.06
Multivariate analysis			
Model from M 4 to 6			
$CO_2 = f$ (WEP, coal, oil, NG)	16.71*	2.96	4.26
CO_2i $= f$ (WEP, coal, oil, NG)	17.21*	2.54	3.91
CO_2t $= f$ (WEP, coal, oil, NG)	15.47*	3.31	4.63

Note: LB: lower bound, UB: upper bound.
*,** indicate level of significance at 1%, 5% and 10%, respectively.

short- and long-term asymmetric coefficients are listed in Tables 7 and 8. The estimated long-term coefficients for WEP_POS and WEP_NEG are 0.013 and –0.007, respectively. It can thus be inferred that a 1-unit increase in the world oil price index leads to an increase of 0.013 units in CO_2 emissions. Similarly, a 1-unit decrease in the world energy price index leads to a CO_2 rise of 0.007 units. The results of the study confirmed the asymmetric relationship between the world energy pricing index and total CO_2 emissions, with a stronger effect of positive changes in WEP on CO_2 emissions than negative changes in WEP.

These findings are consistent with the study by Zhang and Zhang (2016); they also found that oil prices significantly affect China's CO_2 emissions. Nwani (2017) also suggested that the oil prices in Ecuador are increasing CO_2 emissions. The asymmetric

Table 7. Non-linear ARDL estimation results: dependent overall CO_2 emissions per capita (M 1.1 to M 1.4).

Variable	$CO_2 = f$ (WEP) Coefficient (Sig)	$CO_2 = f$ (coal) Coefficient (Sig)	$CO_2 = f$ (oil) Coefficient (Sig)	$CO_2 = f$ (NG) Coefficient (Sig)
CO_2 (-1)	1.311 (0.000)*			
CO_2 (-2)	–0.882 (0.002)*			
CO_2 (-3)	0.583 (0.009)*			
CO_2 (-4)	–0.906 (0.000)*			
WEP_POS	0.009 (0.000)*			
WEP_POS (-1)	–0.005 (0.000)*			
WEP_POS (-2)	0.008 (0.000)*			
WEP_NEG	–0.006 (0.000)*			
C	2.088 (0.000)*			
CO_2 (-1)		1.242 (0.000)*		
coal_POS		0.006 (0.004)*		
coal_NEG		0.000 (0.928)		
coal_NEG (-1)		–0.005 (0.038)**		
C		1.115 (0.003)*		
@TREND		0.0607 (0.001)*		
CO_2 (-1)			1.285 (0.000)*	
CO_2 (-2)			–0.881 (0.002)*	
CO_2 (-3)			0.609 (0.015)**	
CO_2 (-4)			–0.903 (0.000)*	
oil_POS			0.014 (0.000)*	
oil_POS (-1)			–0.008 (0.003)*	
oil_POS (-2)			0.012 (0.000)*	
oil_NEG			–0.009 (0.000)*	
C			2.076 (0.000)*	
@TREND			–0.001 (0.894)	
CO_2 (-1)				1.092 (0.000)*
NG_POS				0.067 (0.064)***
NG_NEG				–0.060 (0.020)**
NG_NEG (-1)				–0.066 (0.007)*
NG_NEG (-3)				0.080 (0.001)*
C				0.8264 (0.013)**
@TREND				0.005 (0.826)

Note: *,**,*** indicate level of significance at 1%, 5% and 10%.

relationship between coal, oil, natural gas and total CO_2 emissions is then evaluated individually. The estimated long-term coefficients for coal_POS and coal_NEG are 0.009 and –0.007, respectively. Therefore, it can be inferred that a 1-unit rise in world coal prices leads to a 0.009 unit rise in CO_2 emissions. Likewise, the 1-unit drop in the coal energy price corresponds to an increase of 0.007 units in CO_2. Whereas, the estimated long-term coefficients for oil_POS and oil_NEG are 0.020 and –0.010, respectively. It implies that a 1-unit increase or decrease in world oil price leads to an increase in overall CO_2 emissions by 0.020 and 0.010 units, respectively. For natural gas prices, the approximate NG_POS and NG_NEG long-term coefficients are 0.167 and –0.212, respectively. This means that total CO_2 emissions in China rise as a result of positive or negative shifts in prices for gas. We found that world energy prices have a non-linear impact on total CO_2 emissions. These findings align with the study by Lim, Lim, and Yoo (2014), Nwani (2017), Saboori, Rasoulinezhad, and Sung (2017) and Ahmad *et al*. (2018). They also found that oil-dependent countries do not change

Table 8. Short-run and long-run asymmetric relationship (M 1.1 to M 1.4).

Variable	$CO_2 = f$ (WEP) Coefficient (Sig)	$CO_2 = f$ (coal) Coefficient (Sig)	$CO_2 = f$ (oil) Coefficient (Sig)	$CO_2 = f$ (NG) Coefficient (Sig)
	Short run			
D(WEP_POS)	0.009 (0.000)*			
D(WEP_NEG)	–0.006 (0.000)*			
CointEq (-1)	–0.893 (0.000)*			
	Log-run			
WEP_POS	0.013 (0.000)*			
WEP_NEG	–0.007 (0.000)*			
C	2.337 (0.000)*			
		Short run		
D(coal_POS)		0.006 (0.004)*		
D(coal_NEG)		0.201 (0.028)**		
CointEq (-1)		–0.613 (0.001)*		
		Log-run		
coal_POS		0.009 (0.000)*		
coal_NEG		–0.007 (0.046)**		
C		1.817 (0.000)*		
			Short run	
D(oil_POS (-1))			–0.012 (0.000)*	
D(oil_NEG)			–0.009 (0.000)*	
			Log run	
oil_POS			0.020 (0.000)*	
oil_NEG			–0.010 (0.000)*	
C			2.333 (0.000)*	
				Short run
D(NG_POS)				0.067 (0.064)***
D(NG_NEG (-1))				–0.088 (0.001)*
CointEq (-1)				–0.403 (0.001)*
				Log-run
NG_POS				0.167 (0.028)**
NG_NEG				–0.212 (0.005)*
C				2.050 (0.000)*

Note: *,**,*** indicate level of significance at 1%, 5% and 10%.

long-term demand for oil, which ultimately increases CO_2. Today, China consumes 12% of world energy and Chinese oil consumption is higher than manufactured, which has adverse effects on higher world energy prices. Fast growth accelerates fuel consumption in China. The recent rise in global energy prices is partly a result of growing energy use in China, which constantly increases CO_2 emissions (Shalizi 2007).

However, for the robustness of the results, we took other CO_2 emissions proxies, including industrial CO_2 emissions and transportation CO_2 emissions, because of their greater contribution to China's total CO_2 emissions.

The dynamic estimate and short- and long-term asymmetric coefficients for CO_2 emissions from the industrial sector are stated in Tables 9 and 10 for Models 2.1 to 2.4, respectively.

The results of industrial CO_2 emissions confirm the insignificant impact of positive change in world energy prices on CO_2 emissions. However, a negative change in world energy prices (world energy prices index, coal, crude oil and natural gas) significantly increases CO_2 emissions. This means that the 1-unit increase in world

Table 9. Non-linear ARDL estimation results: dependent variable CO_2 emissions from the industrial sector (M 2.1 to M 2. 4).

Variable	$CO_2i = f$ (WEP) Coefficient (Sig)	$CO_2i = f$ (coal) Coefficient (Sig)	$CO_2i = f$ (oil) Coefficient (Sig)	$CO_2i = f$ (NG) Coefficient (Sig)
CO_2i (-1)	0.522 (0.088)***			
CO_2i (-3)	0.429 (0.068)***			
WEP_POS	0.014 (0.550)			
WEP_NEG	–0.024 (0.093)***			
C	32.716 (0.035)**			
@TREND	–0.415 (0.388)			
CO_2i (-1)		0.735 (0.000)*		
CO_2i (-3)		0.436 (0.034)**		
coal_POS		0.051 (0.029)**		
coal_POS (-1)		–0.052 (0.058)***		
coal_NEG		–0.090 (0.013)*		
coal_NEG (-1)		0.033 (0.068)**		
C		31.608 (0.009)*		
@TREND		–0.475 (0.113)		
CO_2i (-1)			0.546 (0.079)***	
CO_2i (-3)			0.451 (0.060)***	
oil_POS			0.012 (0.732)	
oil_NEG			–0.031 (0.148)	
C			28.755 (0.060)***	
@TREND			–0.287 (0.563)	
CO_2i (-1)				–0.868 (0.034)**
CO_2i (-2)				0.801 (0.028)**
NG_POS				2.820 (0.002)*
NG_POS (-2)				–1.19 (0.015)*
NG_NEG				–3.581 (0.002)*
NG_NEG (-2)				0.689 (0.027)**
C				140.880 (0.001)*
@TREND				–3.742 (0.004)*

Note: *,**,*** indicate level of significance at 1%, 5% and 10%.

energy prices (world energy prices index, coal, crude oil and natural gas prices) leads to an increase in CO_2 emissions of 0.026, 0.063, 0.037 and 1.65 units. It is also verified, therefore, that in the Chinese case, world energy prices have an asymmetric relationship with CO_2 emissions from the industrial sector.

Chinese growth can lead to an increase in oil prices, which has a stronger impact on its export competitors. These results are also consistent with the work by Fan *et al.* (2007), Faria *et al.* (2009) and Ou, Zhang, and Wang (2012). Error correction terms for Models 2.1 to 2.4 are 93%, 90%, 84% and 57%, respectively; this shows the speed of adjustment of the models. China has become the world's largest oil consumer, and oil imports meet 50% of its oil demand and its imports of oil are continually increasing (Fatima, Xia, and Ahad 2019). China's energy demand is expected to double by 2030. The result shows that as demand and consumption continue to grow, long-term rises in world energy prices do not impact on industrial consumption in China. And declining world energy prices boost Chinese energy consumption with increasing CO_2 emissions. The same pattern has been observed for Chinese coal, crude oil and gas consumption.

Table 10. Short-run and long-run asymmetric relationship (M 2.1 to M 2. 4).

Variable	$CO_2i = f$ (WEP) Coefficient (Sig)	$CO_2i = f$ (coal) Coefficient (Sig)	$CO_2i = f$ (oil) Coefficient (Sig)	$CO_2i = f$ (NG) Coefficient (Sig)
	Short run			
D(WEP_POS)	0.014 (0.550)			
D(WEP_NEG)	–0.024 (0.097)***			
CointEq (-1)	–0.937 (0.019)*			
	Log run			
WEP_POS	0.015 (0.478)			
WEP_NEG	–0.026 (0.010)*			
		Short run		
D(coal_POS)		0.051 (0.029)**		
D(coal_NEG)		–0.090 (0.013)*		
CointEq (-1)		–0.906 (0.004)*		
		Log run		
coal_POS		–0.001 (0.962)		
coal_NEG		–0.063 (0.026)**		
			Short run	
D(oil_POS)			0.012 (0.732)	
D(oil_NEG)			–0.031 (0.148)	
CointEq (-1)			–0.842 (0.032)**	
			Log run	
oil_POS			0.0149 (0.701)	
oil_NEG			–0.037 (0.026)**	
				Short run
D(NG_POS)				2.820 (0.002)*
D(NG_NEG)				–3.581 (0.002)*
CointEq(-1)				–0.570 (0.001)*
				Log run
NG_POS				–0.061 (0.556)
NG_NEG				–1.653 (0.000)*

Note: *,**,*** indicate level of significance at 1%, 5% and 10%.

Next, we looked at the asymmetric relationship between global energy prices and CO_2 emissions in China's transport sector for a thorough analysis. The dynamic estimate and short- and long-term asymmetric coefficients for CO_2 emissions from the transport sector are given in Tables 11 and 12 for Models 3.1 to 3.4, respectively. These findings confirm that the 1-unit increase in WEP leads to a reduction in CO_2 emissions by 0.017 units, while a negative change in WEP does not significantly affect CO_2 emissions. We also find that a 1-unit increase in the price of coal, crude oil and natural gas has resulted in CO_2 emission reductions, respectively, by –0.018, 0.029 and 0.51 units. Negative price changes in coal, crude oil and natural gas do not significantly affect CO_2 emissions. The speed of adjustment for Models 3.1 to 3.4 is 94%, 62%, 120%, 57%, respectively.

Ultimately, we apply multivariate analysis, as shown in Table 13, to the different models, including total CO_2 emissions and emissions from the manufacturing and transport sectors in China. In Model 4, we explore the asymmetric impact of world energy prices on overall CO_2 emissions. In the long-run, we have found a positive shock in WEP (WEP_POS) with a statistically significant negative coefficient (–0.060) and a negative shock in WEP (WEP_NEG) with a negative coefficient (–0.09), meaning that the 1-unit rise in world energy prices causes CO_2 emissions to drop by 0.06

Table 11. Non-linear ARDL estimation results: dependent variable CO_2 emissions from the transport sector (M 3.1 to M 3.4).

Variable	CO_2t = (WEP) Coefficient (Sig)	CO_2t = (coal) Coefficient (Sig)	CO_2t = (oil) Coefficient (Sig)	CO_2t = (NG) Coefficient (Sig)
CO_2t (-1)	0.437(0.079)***			
CO_2t (-2)	–0.380 (0.111)			
WEP_POS	–0.016 (0.035)**			
WEP_NEG	0.003 (0.418)			
C	3.976 (0.003)*			
@TREND	0.390 (0.015)*			
CO_2t (-1)		0.371 (0.100)		
coal_POS		–0.011 (0.106)		
coal_NEG		–0.002 (0.709)		
C		3.085 (0.007)*		
@TREND		0.188 (0.042)**		
CO_2t (-1)			0.502 (0.020)**	
CO_2t (-2)			–0.435 (0.046)**	
CO_2t (-3)			–0.474 (0.041)**	
oil_POS			0.007 (0.678)	
oil_POS (-1)			–0.035 (0.080)***	
oil_POS (-2)			–0.020 (0.283)	
oil_NEG			0.007 (0.441)	
oil_NEG (-1)			0.010 (0.329)	
C			6.798 (0.000)*	
@TREND			1.001 (0.000)*	
CO_2t (-1)				0.421 (0.035)**
NG_POS				0.103 (0.581)
NG_POS (-1)				–0.399 (0.040)**
C				2.316 (0.018)*
@TREND				0.337 (0.020)**

Note: *,**,*** indicate level of significance at 1%, 5% and 10%.

units in the long term. If we reduce the world energy price by 1 unit, CO_2 emissions will rise by 0.09 units in the long term. Although that is true for coal prices, a 1-unit rise in coal prices contributes to a reduction in CO_2 emissions by 0.01 units. While a 1-unit negative coal price shock raises CO_2 emissions by 0.509 units in the long term. When we see the crude oil prices (oil) relationship it shows that crude oil positive shock (CO_POS) having a positive coefficient (0.144) and is statistically significant. It means that a 1-unit rise in crude oil energy prices would raise total CO_2 emissions by 0.144 units. Although an inverse relationship occurs in the case of a negative shock, it means with a 1-unit decrease in world crude oil prices, total CO_2 emissions rise by 0.144 units. In the case of positive shock natural gas prices, we found that with a 1-unit increase in world natural gas prices, CO_2 emissions will decrease by 0.08 units in the long run. While during the negative shock with a 1-unit decrease in natural gas prices, overall CO_2 emissions will be increased by 1.186 units in the long run. For the case of emissions from the industrial sector, we observed the asymmetric impact of world energy prices on CO_2 emissions. We find that the coefficients of WEP_POS, WEP_NEG, coal_POS, coal_NEG, oil_POS, oil_NEG, NG_POS and NG_NEG –2.818, –0.454, –0.121, –0.090, –0.969, –0.666, –1.303 and –0.393, respectively, show a non-linear association between the variables to be used. Next in Model 6, we checked the asymmetric impact of world energy prices on CO_2 emissions from

Table 12. Short-run and long-run asymmetric relationship (M 3.1 to M 3.4).

Variable	CO_2t = (WEP) Coefficient (Sig)	CO_2t = (Coal) Coefficient (Sig)	CO_2t = (CO) Coefficient (Sig)	CO_2t = (NG) Coefficient (Sig)
	Short run			
D(WEP_POS)	–0.016 (0.035)**			
D(WEP_NEG)	0.003 (0.418)			
CointEq (-1)	–0.943 (0.003)*			
	Log run			
WEP_POS	–0.017 (0.003)*			
WEP_NEG	0.003 (0.397)			
		Short run		
D(coal_POS)		–0.011 (0.106)		
D(coal_NEG)		–0.002 (0.709)		
CointEq (-1)		–0.628 (0.008)*		
		Log run		
coal_POS		–0.018 (0.055)***		
coal_NEG		–0.004 (0.712)		
			Short run	
D(oil_POS (-2))			0.017 (0.213)	
D(oil_NEG)			0.007 (0.441)	
CointEq (-1)			–1.245 (0.000)*	
			Log run	
oil_POS			–0.029 (0.000)*	
oil_NEG			–0.001 (0.803)	
				Short run
D(NG_POS)				0.103 (0.581)
D(NG_NEG)				0.089 (0.453)
CointEq (-1)				–0.578 (0.005)*
				Log run
NG_POS				–0.511 (0.041)**
NG_NEG				0.154 (0.393)

Note: *,**,*** level of significant at 1%, 5% and 10%.

transport. Similarly, the long-run asymmetric outcomes confirmed for WEP_POS, WEP_NEG, coal_POS, coal_NEG, oil_POS, oil_NEG, NG_POS and NG_NEG are –0.518, –1.185, –0.962, –0.703, –1.518, –0.296 and –1.759, respectively.

4.1. Wavelet decomposition based on DWT

After analysis of the non-linear relationship between global energy prices and CO_2 emissions, this study used wavelet analyses. Wavelet-based analysis accommodates series stationary issues (Mishra *et al*. 2019). If series are not stationary, data need not be processed to make the series stationary as required for other traditional cointegration-based econometric models. Figure 1 shows a multi-resolution analysis (MRA) of China's overall CO_2 emissions, manufacturing, transport sector emissions and world energy prices of order $J=6$ using Daubechies' (1992) least asymmetric (LA) wavelet filter MODWT. The orthogonal components (D_1 to D_6) are provided in detail in Figure 1 for the presentation of different regularity components of the actual series and a fluid component (S_6). The graphic analysis of the series shows that, in the short run, all series have several differences, but in the long run, all series are stable, while

Table 13. Non-linear ARDL estimation results: A multivariate analysis M 4 to M 6.

Variable	Overall CO_2 emissions Coefficient (Sig)	CO_2 emissions from the industrial sector Coefficient (Sig)	CO_2 emissions from the transport sector Coefficient (Sig)
CO_2 (-1)	–0.214 (0.000)*	–0.033 (0.000)*	–0.054 (0.000)*
WEP_POS	–0.013 (0.050)**	–0.093 (0.023)**	–0.028 (0.032)**
WEP_NEG	–0.021 (0.000)*	–0.015 (0.015)*	–0.064 (0.005)*
coal_POS	–0.003 (0.031)**	–0.004 (0.001)*	–0.052 (0.000)*
coal_NEG	–0.109 (0.001)*	–0.003 (0.000)*	–0.038 (0.000)*
oil_POS	0.031 (0.003)*	–0.032 (0.000)*	–0.018 (0.003)*
oil_NEG	–0.185 (0.000)*	–0.022 (0.043)**	–0.082 (0.003)*
NG_POS	–0.018 (0.000)*	–0.043 (0.024)**	–0.016 (0.002)*
NG_NEG	–0.254 (0.000)*	–0.013 (0.000)*	–0.095 (0.000)*
@TREND	0.005 (0.023)**	0.005 (0.002)*	0.855 (0.001)*
Long-run asymmetric relationship			
WEP_POS	–0.060 (0.030)**	–2.818 (0.023)**	–0.518 (0.000)*
WEP_NEG	–0.098 (0.000)*	–0.454 (0.002)*	–1.185 (0.000)*
coal_POS	–0.014 (0.000)*	–0.121 (0.032)**	–0.962 (0.000)*
coal_NEG	–0.509 (0.000)*	–0.090 (0.002)*	–0.703 (0.000)*
oil_POS	0.144 (0.000)*	–0.969 (0.004)*	–0.333 (0.000)*
oil_NEG	–0.864 (0.000)*	–0.666 (0.000)*	–1.518 (0.000)*
NG_POS	–0.084 (0.000)*	–1.303 (0.000)*	–0.296 (0.013)*
NG_NEG	–1.186 (0.001)*	–0.393 (0.000)*	1.759 (0.000)*

Note: we have only use long-run coefficients in dynamic and long-run asymmetric estimation in multivariate analysis.
*,**Level of significant at 1%, 5% and 10%.

total CO_2 emissions have a lot of long-term stability relative to industrial and transport emissions.

4.2. *Wavelet pairwise and multiple correlations*

This research also used a wavelet correlation between the proposed variables after MODWT measured variation within variables at different frequencies. The wavelet correlation approach will analyze the association between two series in different time and frequency scales. This work also used a wavelet correlation between proposed variables after MODWT measured variance at different frequencies within variables. The wavelet correlation method analyzes the relationship between two series in different time and frequency scales. This research also used a wavelet correlation between proposed variables after MODWT measured variance within variables at different frequencies. The wavelet correlation approach analyzes two series of relationships in a different time and frequency scale. However, the results indicate that there is a poor association between the short- and medium-term WEP and CO_2 emissions, the very long-term association is positive. However, coal prices have poor short-term correlations and very long-term positive ones, although crude oil and gas prices have the same relationship pattern as world energy prices. The third panel in Figure 2 indicates the link between world energy prices and transport sector CO_2 emissions. Ironically, the findings shifted in the transport market.

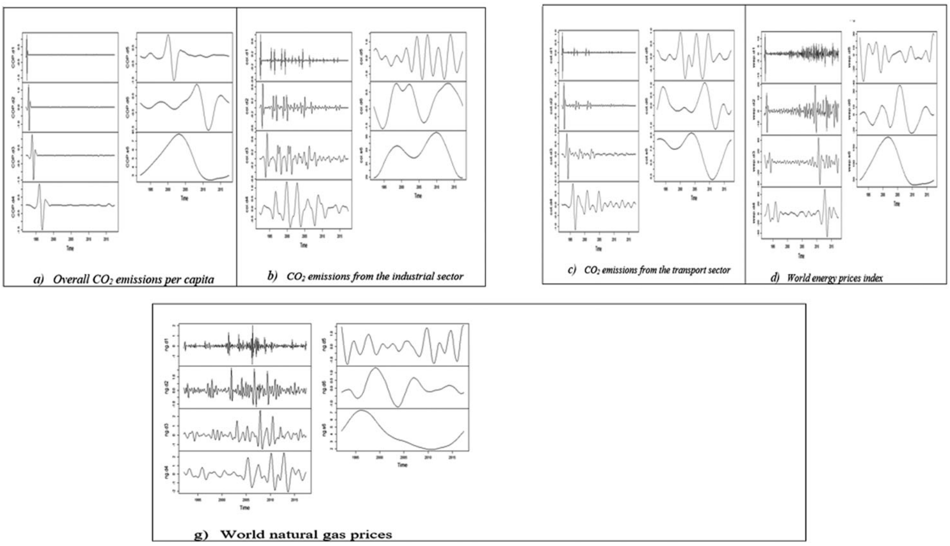

Figure 1. MODWT decomposition on $J = 6$ wavelet levels. Note: D_1 and D_2 indicate short-run, D_3 and D_4 medium run, D_5 and D_6 long-run and S_6 very long-run.

The findings show that there is a positive short-term correlation between the proposed variables, but there is a negative correlation between world energy prices and CO_2 in the long run. We also enriched the wavelet correlation with wavelet multiple correlation findings shown in Figure 3. We consider a strong link between world energy prices and CO_2 emissions over the medium to the very long-term.

4.3. *Wavelet pairwise correlation*

Figure 2 demonstrates the wavelet correlation between world energy prices and CO_2 emissions. Although "U" and "L" signify the upper and lower bound at 95% and the black dotted line displays the correlation between world energy prices and CO_2 emissions.

4.4. *Wavelet-transform coherence*

This research also used wavelet transform coherence (WTC) analysis to check the lead–lag relationship between proposed variables. Based on the cyclic coin of influence (COI) and the anti-cyclical relationship between proposed variables, WTC may provide a proportional period of many time sequences in the present time–frequency space. Figure 4 presents the WTC results for global energy prices and gross CO_2 emissions in China. Figure 4 shows a strong and important short-term (1993–1995) and medium-term (2002–2003) link between world energy prices and CO_2 emissions, although CO_2 emissions are the leading variable. Figure 4b indicates that there is a negative and significant short-term relationship between coal and CO_2 emissions (1998–1999), although CO_2 emissions are a lagging variable. Moreover, the relationship between these factors is very long term, and CO_2 emissions are the leading variable. Figure 4c shows the same relationship pattern between oil and CO_2 emissions as world energy

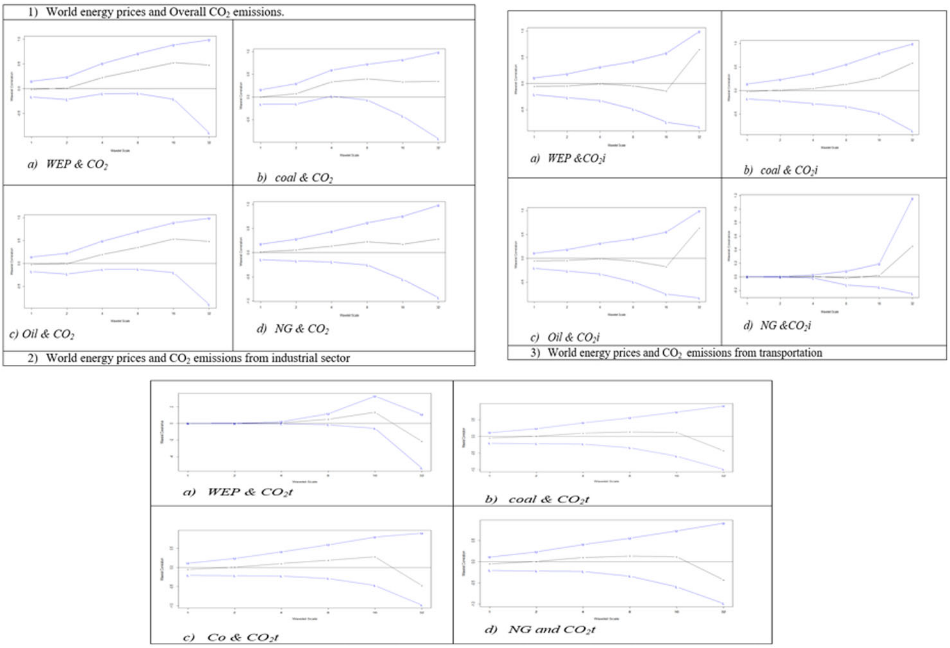

Figure 2. The wavelets correlation between world energy prices and CO_2 emissions. Although "U" and "L" signify the upper and lower bound at 95% and the black dotted line displays the correlation between world energy prices and CO_2 emissions.

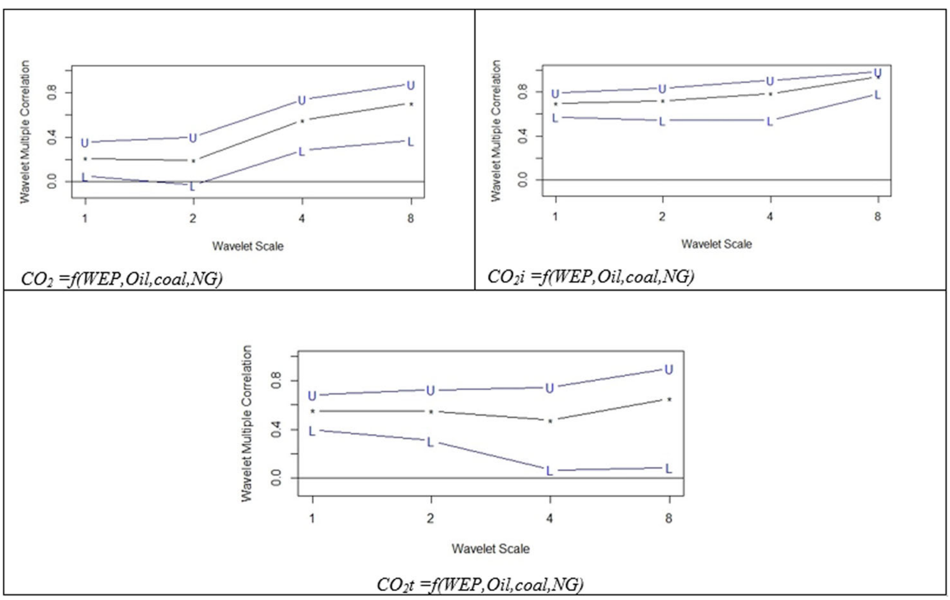

Figure 3. The multiple wavelet correlation between world energy prices and CO_2 emissions. Although "U" and "L" signify the upper and lower bound at 95% and the black dotted line displays the correlation between world energy prices and CO_2 emissions.

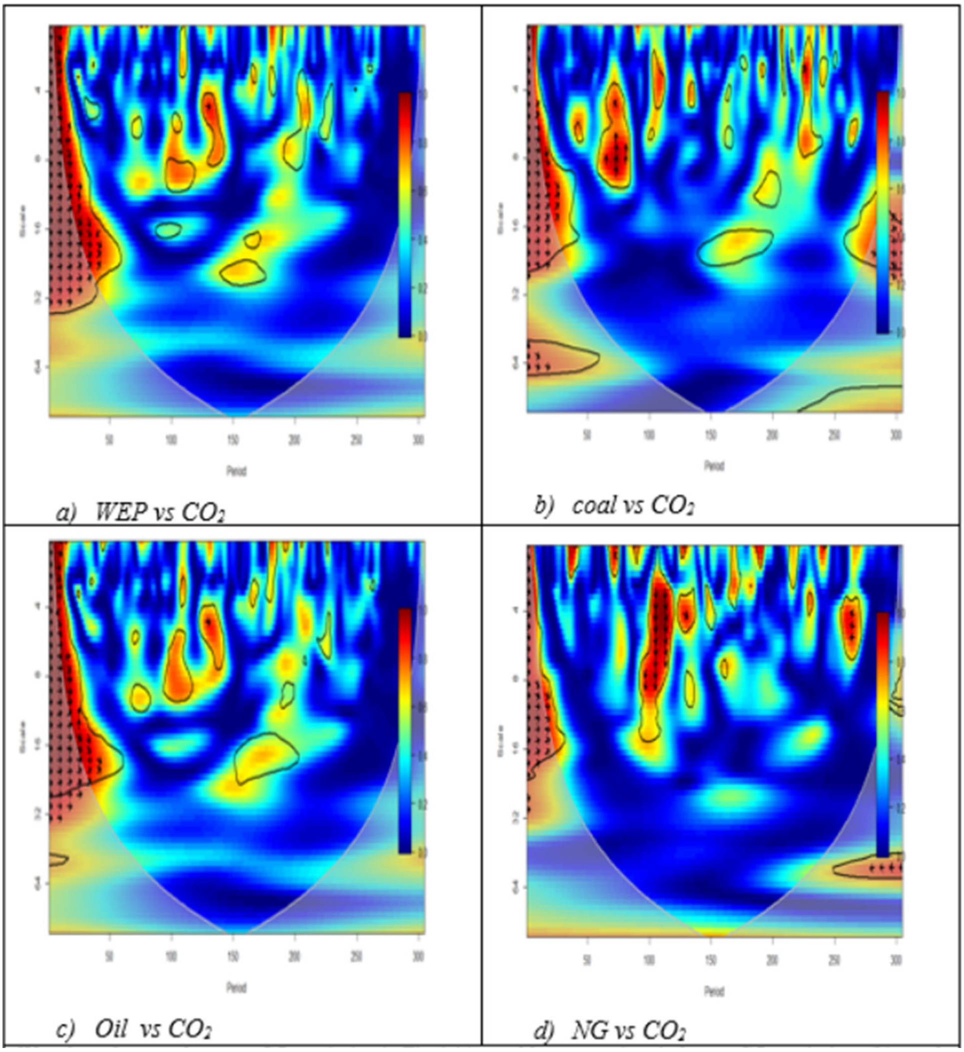

Figure 4. Wavelet coherence between CO_2 emission (a), world energy prices index vs. CO_2 emissions (b), crude oil vs. CO_2 emissions (c), crude oil vs. CO_2 emissions (d) and natural gas vs. CO_2 emissions. The color code for power ranges from blue (low coherence) to red (high coherence). A point-wise significance test is performed against an almost process-independent background spectrum. 95% confidence intervals for the null hypothesis that coherency is zero are plotted as contours in black in the figure. The cone of influence is marked by black lines. The horizontal axis represents sample periods (from 1992 to 2017), the vertical axis refers to the period in various frequencies short-term to very long-term (2–4 months to 64 months).

and CO_2 emissions. However, we note important observations for world natural gas prices and CO_2 emissions in Figure 4d; in the short term, natural gas prices adversely and substantially correlate with CO_2 emissions, while CO_2 performs as a lagging variable. However, a medium-term positive relationship exists between NG and CO_2, and CO_2 is a leading indicator.

Other CO_2 emission indicators were also used to monitor robustness, such as emissions from China's manufacturing sector and transport sector, as these two sectors are

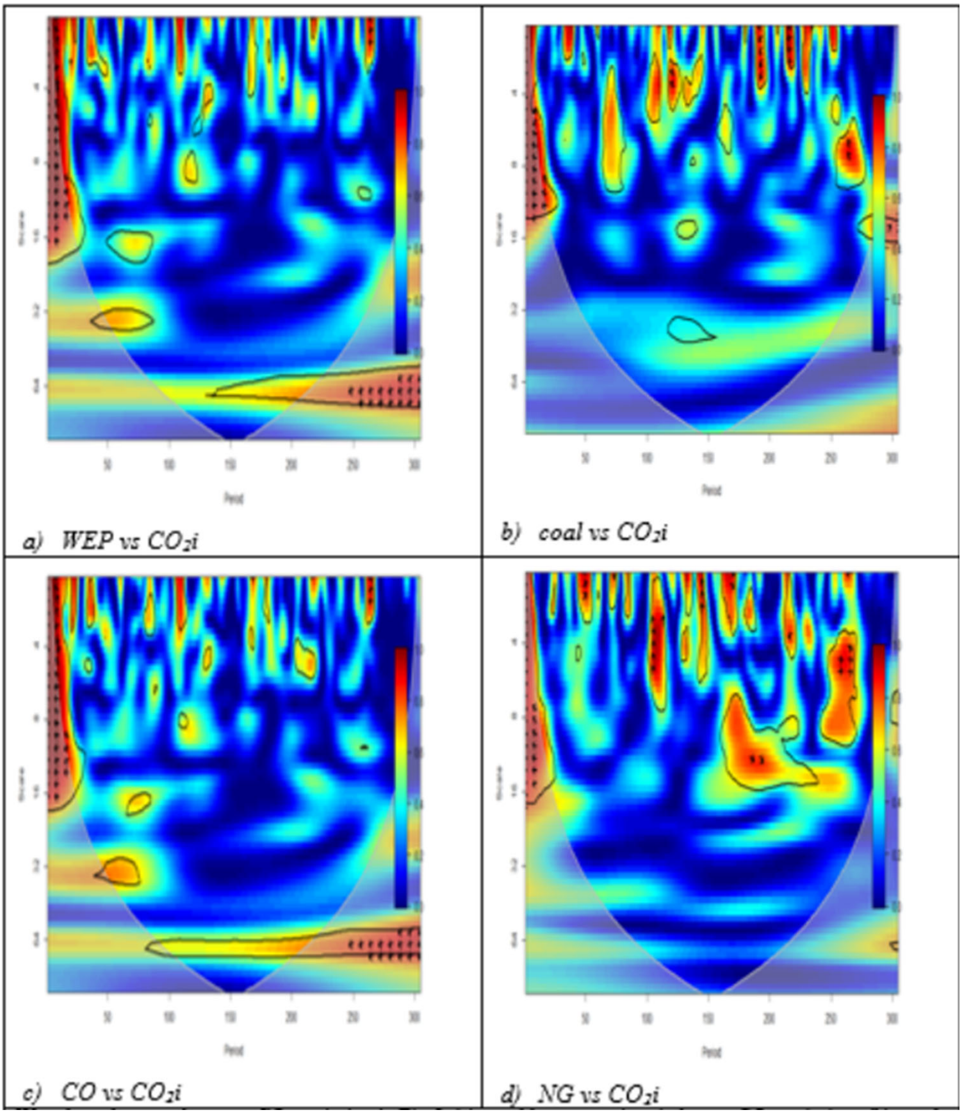

Figure 5. Wavelet coherence between CO_2 emission (a), world energy prices index vs. CO_2 emissions (b), crude oil vs. CO_2 emissions (c), crude oil vs. CO_2 emissions (d) and natural gas vs. CO_2 emissions. The color code for power ranges from blue (low coherence) to red (high coherence). A point-wise significance test is performed against an almost process-independent background spectrum. 95% confidence intervals for the null hypothesis that coherency is zero are plotted as contours in black in the figure. The cone of influence is marked by black lines.

major CO_2 contributors in China. Figure 5 reveals the WTC figures for world energy and industrial CO_2 emissions.

Figure 5a shows a negative association between WEP and CO_2 emissions in short and medium runs, and WEP is the leading indicator. For coal prices in Figure 5b, we consider a negative correlation between these variables in short and medium terms, and coal is a leading variable. In Figure 5c there is a negative short-run association

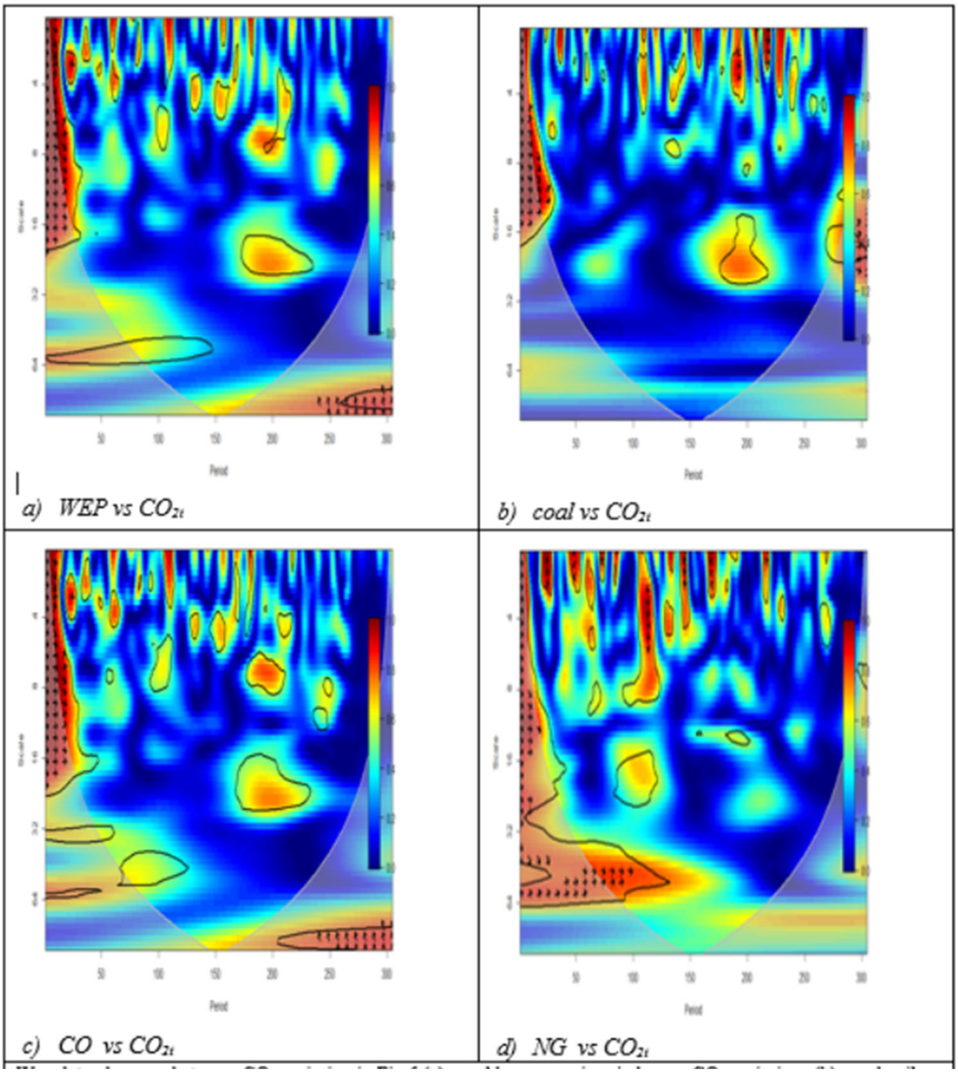

Figure 6. Wavelet coherence between CO_2 emission (a), world energy prices index vs. CO_2 emissions (b), crude oil vs. CO_2 emissions (c), crude oil vs. CO_2 emissions, (d) and natural gas vs. CO_2 emissions. The color code for power ranges from blue (low coherence) to red (high coherence). A point-wise significance test is performed against an almost process-independent background spectrum. 95% confidence intervals for the null hypothesis that coherency is zero are plotted as contours in black in the figure. The cone of influence is marked by black lines.

between crude oil and CO_2 emissions, and oil is the leading indicator. However, Figure 5d indicates that there is a positive relationship between gas prices and CO_2 emissions in the short and medium term, although CO_2 emissions are a leading variable. Figure 6a–d shows WTC results for world energy prices and transport CO_2 emissions. A negative link between global resources, coal, crude oil prices and CO_2 emissions and world energy prices leads in the short run. Although natural gas prices and CO_2 emissions are positive in the very long-term, CO_2 emissions are the leading variables.

5. Conclusion

This study analyzes the asymmetric and time-varying effect on China's environmental deterioration of world energy prices. World energy prices include the world energy price index, world crude oil prices, world coal prices and world gas prices, and environmental pollution was calculated using global CO_2 emissions, industrial CO_2 emissions and transport emissions. This research uses monthly data from 1992 to 2017. Considering the significance of non-linearities and time and frequency domains, this study used wavelet-based analyses (for time–frequency) and non-linear ARDL (NARDL) approaches (for negative and positive changes) that consider short-term instabilities and sudden changes and to provide short-run and long-run non-linear interaction between the variables proposed. The results based on NARDL modeling indicated an asymmetric relationship between world energy prices (including the world energy price index, coal, oil and natural gas prices) and long-term total CO_2 emissions. Positive changes in world energy prices have a greater impact on CO_2 emissions compared to a negative change. Either global energy prices are rising or dropping, China's total CO_2 emissions are increasing in both circumstances. We find that significant improvements in prices of global energy had no impact on CO_2 emissions from the industrial sector. Nevertheless, declines in world energy prices (including the world energy price index, crude oil, coal, and natural gas prices) dramatically raise CO_2 emissions. Nevertheless, in the case of transport sector CO_2 emissions, we have noticed that a positive shift in world energy prices has contributed to a decrease in CO_2 emissions, but a negative shift in world energy prices does not significantly affect emissions. This research also uses a wavelet-based correlation technique to investigate time-varying effects between aim variables. The results indicate a clear positive association between world energy prices, total CO_2 emissions and industrial CO_2 emissions in the very long-term. Nevertheless, global oil prices and transport-industry CO_2 have a long-term negative correlation. Moreover, wavelet multiple correlations indicate strong overall.

This research also uses a wavelet-correlation technique to investigate time-between aim variables. The results indicate a clear positive association between world energy prices, total CO_2 emissions and industrial CO_2 emissions in the very long-term. Nevertheless, global oil prices and transport-CO_2 have a long-negative correlation. However, wavelet multiple correlations indicate an overall positive association between world energy prices and CO_2 emissions in all cases (overall CO_2 emissions from the manufacturing sector and transport system). Moreover, one of the possible effects of higher CO_2 due to higher oil prices is moving to cheaper energy supply such as gas, and fuel subsidy often absorbs price effects. Evidence suggests that ignoring inherent non-linearities can lead to a misleading inference. Evidence of asymmetry and time and frequency domain could be of major importance in making climate policy decisions more efficient and forecasting China's CO_2 emissions. Finally, this study may recommend that authorities adopt demand-side management policies considering energy demand actions in both shorter and longer cycles to minimize CO_2 emissions in China. Decades of rapid growth have significantly increased China's energy needs. China is the world's largest electricity user, the largest coal producer and consumer, and the largest carbon dioxide emitter. Zeng *et al.* (2018) found that the Chinese energy industry's overall investment performance is relatively poor. During the past half-century, non-renewable energy has largely fueled China's massive manufacturing-based economy.

5.1. Policy implications

Based on the findings reviewed, it is recommended that China build energy efficiency to gradually upgrade the energy sectors from conventional energy sources to improved renewable energy production tools to help reduce CO_2 emissions. Refining energy efficiency and converting conventional energy production capacity from coal and other traditional energy sources to renewable energy resources will increase energy sector performance and help reduce CO_2 emissions.

On the basis of outcomes of wavelet analysis, this study suggests that there is a dire need to switch from conventional sources of energy such as non-renewable to renewable energy/green energy/pollution-free energy gradually in the long run, such as solar energy, wind power, hydroelectric energy etc. If China suddenly changes energy consumption behavior toward renewable energy, China will face substantial economic loss; therefore, a slow shifting is more beneficial. Green innovations can be the best climate-efficient sources of green growth by (1) improving industrial productivity by increasing renewable energy and reducing the negative ecological effects; (b) expanding new green industries, such as renewable energy, clean cars and waste management and (c) leapfrogging current technology to give rise to new industries. Besides, the research carried out recently by Arain, Han, and Meo (2019) argued that we can obtain misleading results in the presence of cross-sectional dependence. Therefore, it is suggested that researchers perform panel studies considering the cross-sectional dependence issues.

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References

AhAtil, A., F. B. Bouheni, A. Lahiani, and M. Shahbaz. 2019. "Factors Influencing CO_2 Emission in China: A Nonlinear Autoregressive Distributed Lags Investigation." MPRA. https://mpra.ub.uni-muenchen.de/id/eprint/91190.

Ahmad, M., Z. Khan, Z. Ur Rahman, and S. Khan. 2018. "Does Financial Development Asymmetrically Affect CO_2 Emissions in China? An Application of the Nonlinear Autoregressive Distributed Lag (NARDL) Model." *Carbon Management* 9 (6): 631–644. doi:10.1080/17583004.2018.1529998.

Ahmad, N., and L. Du. 2017. “Effects of Energy Production and CO_2 Emissions on Economic Growth in Iran: ARDL Approach.” *Energy* 123: 521–537. doi:10.1016/j.energy.2017.01.144.
Al-Mulali, U., and I. Ozturk. 2016. “The Investigation of the Environmental Kuznets Curve Hypothesis in the Advanced Economies: The Role of Energy Prices.” *Renewable and Sustainable Energy Reviews* 54: 1622–1631. doi:10.1016/j.rser.2015.10.131.
Alshehry, A. S., and M. Belloumi. 2017. “Study of the Environmental Kuznets Curve for Transport Carbon Dioxide Emissions in Saudi Arabia.” *Renewable and Sustainable Energy Reviews* 75: 1339–1347. doi:10.1016/j.rser.2016.11.122.
Alvarado, R., P. Ponce, A. Criollo, K. Córdova, and M. K. Khan. 2018. “Environmental Degradation and Real per Capita Output: New Evidence at the Global Level Grouping Countries by Income Levels.” *Journal of Cleaner Production* 189: 13–20. doi:10.1016/j.jclepro.2018.04.064.
Amano, A. 1990. “Energy Prices and CO_2 Emissions in the 1990s.” *Journal of Policy Modeling* 12 (3): 495–510. doi:10.1016/0161-8938(90)90010-C.
Anoruo, E. 2011. “Testing for Linear and Nonlinear Causality Between Crude Oil Price Changes and Stock Market Returns.” *International Journal of Economic Sciences and Applied Research* 4 (3): 75–92. http://ijbesar.teiemt.gr/docs/volume4_issue3/crude_oil_price_changes.pdf.
Arain, H., L. Han, and M. S. Meo. 2019. “Nexus of FDI, Population, Energy Production, and Water Resources in South Asia: A Fresh Insight from Dynamic Common Correlated Effects (DCCE).” *Environmental Science and Pollution Research International* 26 (26): 27128–27137. doi:10.1007/s11356-019-05903-7.
Awan, S. A., M. S. Meo, A. Ghimire, R. Y. Wu, and P. F. Zhuang. 2018. “Is Trade Openness Good or Bad for Environment in Pakistan; an ARDL Bounds Testing Approach.” Paper presented at the 4th Annual International Conference on Management, Economics and Social Development (ICMESD 2018), Xi’an, Shaanxi, China, May 18–20. doi:10.2991/icmesd-18.2018.142.
Azam, M., A. Q. Khan, and I. Ozturk. 2019. “The Effects of Energy on Investment, Human Health, Environment, and Economic Growth: Empirical Evidence from China.” *Environmental Science and Pollution Research International* 26 (11): 10816–10825. https://link.springer.com/article/10.1007%2Fs11356-019-04497-4. doi:10.1007/s11356-019-04497-4.
Bai, Y. P., and J. Yang. 2012. “Energy Consumption-Economic Growth Relationship and Carbon Emissions in Twelve Provinces of the West of China.” *Applied Mechanics and Materials* 178–181: 885–892. doi:10.4028/www.scientific.net/AMM.178-181.885.
Bildirici, M. E., and C. Turkmen. 2015. “Nonlinear Causality Between Oil and Precious Metals.” *Resources Policy* 46: 202–211. doi:10.1016/j.resourpol.2015.09.002.
Bilgili, F., E. Mugaloglu, and E. Koçak. 2018. “The Impact of Oil Prices on CO_2 Emissions in China: A Wavelet Coherence Approach.” MPRA. https://mpra.ub.uni-muenchen.de/id/eprint/90170.
Blazquez, J., J. M. Martin-Moreno, R. Perez, and J. Ruiz. 2017. “Fossil Fuel Price Shocks and CO2 Emissions: The Case of Spain.” *The Energy Journal* 38 (01): 161–177. doi:10.5547/01956574.38.6.jmar.
Boufateh, T. 2019. “The Environmental Kuznets Curve by Considering Asymmetric Oil Price Shocks: Evidence from the Top Two.” *Environmental Science and Pollution Research International* 26 (1): 706–720. doi:10.1007/s11356-018-3641-3.
Chai, J., Q. Y. Lu, S. Y. Wang, and K. K. Lai. 2016. “Analysis of Road Transportation Energy Consumption Demand in China.” *Transportation Research Part D: Transport and Environment* 48: 112–124. doi:10.1016/j.trd.2016.08.009.
Chai, J., Y. Zhou, T. Liang, L. Xing, and K. Lai. 2016. “Impact of International Oil Price on Energy Conservation and Emission Reduction in China.” *Sustainability* 8 (6): 508. doi:10.3390/su8060508.
Chang, B. H., M. S. Meo, Q. R. Syed, and Z. Abro. 2019. “Dynamic Analysis of the Relationship Between Stock Prices and Macroeconomic Variables.” *South Asian Journal of Business Studies* 8 (3): 229–245. doi:10.1108/SAJBS-06-2018-0062.
Chang, C. C. 2010. “A Multivariate Causality Test of Carbon Dioxide Emissions, Energy Consumption and Economic Growth in China.” *Applied Energy* 87 (11): 3533–3537. doi:10.1016/j.apenergy.2010.05.004.

Cheng, C., X. Ren, Z. Wang, and C. Yan. 2019. “Heterogeneous Impacts of Renewable Energy and Environmental Patents on CO_2 Emission: Evidence from the BRICS.” *Science of the Total Environment* 668: 1328–1338. doi:10.1016/j.scitotenv.2019.02.063.

Cong, R.-G., Y.-M. Wei, J.-L. Jiao, and Y. Fan. 2008. “Relationships Between Oil Price Shocks and Stock Market: An Empirical Analysis from China.” *Energy Policy* 36 (9): 3544–3553. doi:10.1016/j.enpol.2008.06.006.

Daubechies, I. 1992. *Ten Lectures on Wavelets* (Vol. 61). Philadelphia, PA: Society for Industrial and Applied Mathematics.

Fan, Y., J. Jiao, Q. Liang, Z. Y. Han, and Y. Wei. 2007. “The Impact of Rising International Crude Oil Price on China’s Economy: An Empirical Analysis with CGE Model.” *International Journal of Global Energy Issues* 27 (4): 404. doi:10.1504/IJGEI.2007.014864.

Fareed, Z., M. S. Meo, B. Zulfiqar, F. Shahzad, and N. Wang. 2018. “Nexus of Tourism, Terrorism, and Economic Growth in Thailand: New Evidence from Asymmetric ARDL Cointegration Approach.” *Asia Pacific Journal of Tourism Research* 23 (12): 1129–1141. doi:10.1080/10941665.2018.1528289.

Faria, J. R., A. V. Mollick, P. H. Albuquerque, and M. A. León-Ledesma. 2009. “The Effect of Oil Price on China’s Exports.” *China Economic Review* 20 (4): 793–805. doi:10.1016/j.chieco.2009.04.003.

Fatima, T., E. Xia, and M. Ahad. 2018a. “An Aggregate and Disaggregate Energy Consumption, Industrial Growth, and CO_2 Emission: Fresh Evidence from Structural Breaks and Combined Cointegration for China.” *International Journal of Energy Sector Management* 12 (1): 130–150. doi:10.1108/IJESM-08-2017-0007.

Fatima, T., E. Xia, and M. Ahad. 2018b. “Oil Demand Forecasting for China: Fresh Evidence from Structural Time Series Analysis.” *Environment, Development, and Sustainability* 21 (3): 1205–1224. https://link.springer.com/article/10.1007/s10668-018-0081-7.

Fatima, T., E. Xia, Z. Cao, D. Khan, and J. L. Fan. 2019. “Decomposition Analysis of Energy-Related CO_2 Emission in the Industrial Sector of China: Evidence from the LMDI Approach.” *Environmental Science and Pollution Research International* 26 (21): 21736–21749. doi:10.1007/s11356-019-05468-5.

Fei, L., S. Dong, L. Xue, Q. Liang, and W. Yang. 2011. “Energy Consumption-Economic Growth Relationship and Carbon Dioxide Emissions in China.” *Energy Policy* 39 (2): 568–574. doi:10.1016/j.enpol.2010.10.025.

Fei, Q., and R. Rasiah. 2014. “Electricity Consumption, Technological Innovation, Economic Growth and Energy Prices: Does Energy Export Dependency and Development Levels Matter?” *Energy Procedia* 61: 1142–1145. doi:10.1016/j.egypro.2014.11.1041.

Feng, T., L. Sun, and Y. Zhang. 2009. “The Relationship Between Energy Consumption Structure, Economic Structure, and Energy Intensity in China.” *Energy Policy* 37 (12): 5475–5483. doi:10.1016/j.enpol.2009.08.008.

Granger, C. W., and G. Yoon. 2002. *Hidden Cointegration*. Economics Working Paper, (2002-02). University of California. https://dx.doi.org/10.2139/ssrn.313831

Hammoudeh, S., A. Lahiani, D. K. Nguyen, and R. M. Sousa. 2015. “An Empirical Analysis of Energy Cost Pass-Through to CO_2 Emission Prices.” *Energy Economics* 49: 149–156. doi:10.1016/j.eneco.2015.02.013.

Haug, A. A., and M. Ucal. 2019. “The Role of Trade and FDI for CO_2 Emissions in Turkey: Nonlinear Relationships.” *Energy Economics* 81: 297–307. doi:10.1016/j.eneco.2019.04.006.

He, Z., S. Xu, W. Shen, R. Long, and H. Chen. 2017. “Impact of Urbanization on Energy-Related CO_2 Emission at Different Development Levels: Regional Difference in China Based on Panel Estimation.” *Journal of Cleaner Production* 140: 1719–1730. doi:10.1016/j.jclepro.2016.08.155.

Huang, X., H. An, X. Gao, X. Hao, and P. Liu. 2015. “Multiresolution Transmission of the Correlation Modes Between Bivariate Time Series Based on Complex Network Theory.” *Physica A: Statistical Mechanics and Its Applications* 428: 493–506. doi:10.1016/j.physa.2015.02.028.

Jalil, A., M. Feridun, and Y. Ma. 2010. “Finance-Growth Nexus in China Revisited: New Evidence from Principal Components and ARDL Bounds Tests.” *International Review of Economics & Finance* 19 (2): 189–195. doi:10.1016/j.iref.2009.10.005.

Kahneman, D. and A. Tversky. 1979. “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica* 47 (2): 263–291.

Khan, M. K., J. Z. Teng, and M. I. Khan. 2019a. “Asymmetric Impact of Oil Prices on Stock Returns in Shanghai Stock Exchange: Evidence from Asymmetric ARDL Model.” *PLoS One* 14 (6): e0218289. doi:10.1371/journal.pone.0218289.

Khan, M. K., J. Z. Teng, and M. I. Khan. 2019b. “Effect of Energy Consumption and Economic Growth on Carbon Dioxide Emissions in Pakistan with Dynamic ARDL Simulations Approach.” *Environmental Science and Pollution Research International* 26 (23): 23480–23490. doi:10.1007/s11356-019-05640-x.

Li, D., and D. Yang. 2016. “Does Non-Fossil Energy Usage Lower CO_2 Emissions? Empirical Evidence from China.” *Sustainability* 8 (9): 874. doi:10.3390/su8090874.

Li, H., B. Li, and H. Lu. 2017. “Carbon Dioxide Emissions, Economic Growth, and Selected Types of Fossil Energy Consumption in China: Empirical Evidence from 1965 to 2015.” *Sustainability* 9 (5): 697. 10.3390/su9050697.

Li, K., L. Fang, and L. He. 2019. “How the Population and Energy Price Affects China’s Environmental Pollution?” *Energy Policy* 129: 386–396. doi:10.1016/j.enpol.2019.02.020.

Li, M., Z. Mi, D. M. Coffman, and Y. M. Wei. 2018. “Assessing the Policy Impacts on Non-Ferrous Metals Industry’s CO_2 Reduction: Evidence from China.” *Journal of Cleaner Production* 192: 252–261. doi:10.1016/j.jclepro.2018.05.015.

Lim, K. M., S. Y. Lim, and S. H. Yoo. 2014. “Oil Consumption, CO_2 Emission, and Economic Growth: Evidence from the Philippines.” *Sustainability* 6 (2): 967–979. doi:10.3390/su6020967.

Liu, Z., D. Guan, W. Wei, S. J. Davis, P. Ciais, J. Bai, S. Peng, *et al.* 2015. “Reduced Carbon Emission Estimates from Fossil Fuel Combustion and Cement Production in China.” *Nature* 524 (7565): 335–338. doi:10.1038/nature14677.

Long, S., and J. Liang. 2018. “Asymmetric and Nonlinear Pass-Through of Global Crude Oil Price to China’s PPI and CPI Inflation.” *Economic Research – Ekonomska Istraživanja* 31 (1): 240–251. doi:10.1080/1331677X.2018.1429292.

Long, X., E. Y. Naminse, J. Du, and J. Zhuang. 2015. “Nonrenewable Energy, Renewable Energy, Carbon Dioxide Emissions and Economic Growth in China from 1952 to 2012.” *Renewable and Sustainable Energy Reviews* 52: 680–688. doi:10.1016/j.rser.2015.07.176.

Maji, I K., M S. Habibullah, M Y. Saari, and A S. Abdul-Rahim. 2017. “The Nexus Between Energy Price Changes and Environmental Quality in Malaysia.” *Energy Sources Part B: Economics, Planning, and Policy* 12 (10): 903–909. doi:10.1080/15567249.2017.1323052.

Martinsen, D., V. Krey, and P. Markewitz. 2007. “Implications of High Energy Prices for Energy System and Emissions: The Response from an Energy Model for Germany.” *Energy Policy* 35 (9): 4504–4515. doi:10.1016/j.enpol.2007.03.003.

Masood, J., F. Farooq, and M. Saeed. 2015. “CO_2 and Environment Change Evidence from Pakistan.” *Review of Economics and Development Studies* 1 (2): 57–72. doi:10.26710/reads.v1i2.116.

Meo, M. S., M. A. F. Chowdhury, G. M. Shaikh, M. Ali, and S. Masood Sheikh. 2018a. “Asymmetric Impact of Oil Prices, Exchange Rate, and Inflation on Tourism Demand in Pakistan: New Evidence from Nonlinear ARDL.” *Asia Pacific Journal of Tourism Research* 23 (4): 408–422. doi:10.1080/10941665.2018.1445652.

Meo, M. S., V. J. Khan, T. O. Ibrahim, S. Khan, S. Ali, and K. Noor. 2018b. “Asymmetric Impact of Inflation and Unemployment on Poverty in Pakistan: New Evidence from Asymmetric ARDL Cointegration.” *Asia Pacific Journal of Social Work and Development* 28 (4): 295–310. doi:10.1080/02185385.2018.1523745.

Mishra, S., A. Sharif, S. Khuntia, S. A. Meo, and S. A. R. Khan. 2019. “Do Oil Prices Impede Islamic Stock Indices? Fresh Insights from Wavelet-Based Quantile-on-Quantile Approach.” *Resources Policy* 62: 292–304. doi:10.1016/j.resourpol.2019.04.005.

Nie, Y., P. Chen, T. Zhang, and E. Wang. 2019. “Impacts of International Oil Price Fluctuations on China’s PM2. 5 Concentrations: A Wavelet Analysis.” *Economic Research – Ekonomska Istraživanja* 1–21. doi:10.1080/1331677X.2019.1656098.

Nwani, C. 2017. “Causal Relationship Between Crude Oil Price, Energy Consumption and Carbon Dioxide (CO_2) Emissions in Ecuador.” *OPEC Energy Review* 41 (3): 201–225. doi:10.1111/opec.12102.

Ou, B., X. Zhang, and S. Wang. 2012. “How Does China’s Macro-Economy Response to the World Crude Oil Price Shock: A Structural Dynamic Factor Model Approach.” *Computers & Industrial Engineering* 63 (3): 634–640.

Ozturk, I., and A. Acaravci. 2016. “Energy Consumption, CO_2 Emissions, Economic Growth, and Foreign Trade Relationship in Cyprus and Malta.” *Energy Sources Part B: Economics, Planning, and Policy* 11 (4): 321–327. doi:10.1080/15567249.2011.617353.

Payne, J. E. 2012. “The Causal Dynamics Between US Renewable Energy Consumption, Output, Emissions, and Oil Prices.” *Energy Sources Part B: Economics, Planning, and Policy* 7 (4): 323–330. doi:10.1080/15567249.2011.595248.

Pesaran, M. H., Y. Shin, and R. J. Smith. 2001. “Bounds Testing Approaches to the Analysis of Level Relationships.” *Journal of Applied Econometrics* 16 (3): 289–326. doi:10.1002/jae.616.

Po, W. C., and B. N. Huang. 2008. “Tourism Development and Economic Growth: A Nonlinear Approach.” *Physica A: Statistical Mechanics and Its Applications* 387 (22): 5535–5542. doi:10.1016/j.physa.2008.05.037.

Power, G. J., and C. G. Turvey. 2010. “Long-Range Dependence in the Volatility of Commodity Futures Prices: Wavelet-Based Evidence.” *Physica A: Statistical Mechanics and Its Applications* 389 (1): 79–90. doi:10.1016/j.physa.2009.08.037.

Rahman, Z. U., and M. Ahmad. 2019. “Modeling the Relationship Between Gross Capital Formation and CO_2 (a) Symmetrically in the Case of Pakistan: An Empirical Analysis Through NARDL Approach.” *Environmental Science and Pollution Research* 26 (8): 8111–8114. https://link.springer.com/article/10.1007%2Fs11356-019-04254-7. doi:10.1007/s11356-019-04254-7.

Rasheed, R., M. S. Meo, R. U. Awan, and F. Ahmed. 2019. “The Impact of Tourism on Deficit in Balance of Payments of Pakistan: An Application of Bounds Testing Approach to Cointegration.” *Asia Pacific Journal of Tourism Research* 24 (4): 325–332. doi:10.1080/10941665.2018.1564345.

Saboori, B., E. Rasoulinezhad, and J. Sung. 2017. “The Nexus of Oil Consumption, CO2 Emissions and Economic Growth in China, Japan and South Korea.” *Environmental Science and Pollution Research International* 24 (8): 7436–7455. https://link.springer.com/article/10.1007/s11356-017-8428-4. doi:10.1007/s11356-017-8428-4.

Salim, R. A., and S. Rafiq. 2012. “Why Do Some Emerging Economies Proactively Accelerate the Adoption of Renewable Energy?” *Energy Economics* 34 (4): 1051–1057. doi:10.1016/j.eneco.2011.08.015.

Schorderet, Y. 2003. *Asymmetric Cointegration*. Genève: Université de Genève/Faculté des sciences économiques et sociales.

Shalizi, Z. 2007. “Energy and Emissions: Local and Global Effects of the Rise of China and India.” The World Bank. http://siteresources.worldbank.org/INTCHIINDGLOECO/Resources/CE_ch05pp.117-156_FINAL.pdf

Shin, Y., B. Yu, and M. Greenwood-Nimmo. 2014. “Modeling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework.” In *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*, edited by Robin Sickles, and William C. Horrace, 281–314. New York, NY: Springer. https://link.springer.com/chapter/10.1007/978-1-4899-8008-3_9.

Sun, M., Y. Wang, L. Shi, and J. J. Klemeš. 2018. “Uncovering Energy Use, Carbon Emissions and Environmental Burdens of Pulp and Paper Industry: A Systematic Review and Meta-Analysis.” *Renewable and Sustainable Energy Reviews* 92: 823–833. doi:10.1016/j.rser.2018.04.036.

Torrence, C., and P. J. Webster. 1999. “Interdecadal Changes in the ENSO Monsoon System.” *Journal of Climate* 12 (8): 2679–2690. https://doi.org/10.1175/1520-0442(1999)012%3C2679:ICITEM%3E2.0.CO;2

Wang, Q., and R. Jiang. 2019. “Is China’s Economic Growth Decoupled from Carbon Emissions?” *Journal of Cleaner Production* 225: 1194–1208. doi:10.1016/j.jclepro.2019.03.301.

Wang, Q., and M. Su. 2020. “Drivers of Decoupling Economic Growth from Carbon Emission: An Empirical Analysis of 192 Countries Using Decoupling Model and Decomposition Method.” *Environmental Impact Assessment Review* 81: 106356. doi:10.1016/j.eiar.2019.106356.

Wang, Q., M. Su, R. Li, and P. Ponce. 2019. “The Effects of Energy Prices, Urbanization and Economic Growth on Energy Consumption Per Capita in 186 Countries.” *Journal of Cleaner Production* 225: 1017–1032. doi:10.1016/j.jclepro.2019.04.008.

Wang, Q., and F. Zhang. 2020. “Does Increasing Investment in Research and Development Promote Economic Growth Decoupling from Carbon Emission Growth? An Empirical Analysis of BRICS Countries.” *Journal of Cleaner Production* 252: 119853. doi:10.1016/j.jclepro.2019.119853.

Wang, S., C. Fang, X. Guan, B. Pang, and H. Ma. 2014. “Urbanization, Energy Consumption, and Carbon Dioxide Emissions in China: A Panel Data Analysis of China’s Provinces.” *Applied Energy* 136: 738–749. doi:10.1016/j.apenergy.2014.09.059.

Wang, S., G. Li, and C. Fang. 2018. “Urbanization, Economic Growth, Energy Consumption, and CO_2 Emissions: Empirical Evidence from Countries with Different Income Levels.” *Renewable and Sustainable Energy Reviews* 81: 2144–2159. doi:10.1016/j.rser.2017.06.025.

Wang, S., Q. Li, C. Fang, and C. Zhou. 2016. “The Relationship Between Economic Growth, Energy Consumption, and CO_2 Emissions: Empirical Evidence from China.” *The Science of the Total Environment* 542 (Part A): 360–371. doi:10.1016/j.scitotenv.2015.10.027.

Wang, X., M. Bai, and C. Xie. 2019. “Investigating CO_2 Mitigation Potentials and the Impact of Oil Price Distortion in China’s Transport Sector.” *Energy Policy* 130: 320–327. doi:10.1016/j.enpol.2019.04.003.

Winchester, N., and K. Ledvina. 2017. “The Impact of Oil Prices on Bioenergy, Emissions, and Land Use.” *Energy Economics* 65: 219–227. doi:10.1016/j.eneco.2017.05.008.

Yang, D., and H. Timmermans. 2012. “Effects of Fuel Price Fluctuation on Individual CO_2 Traffic Emissions: Empirical Findings from Pseudo Panel Data.” *Procedia – Social and Behavioral Sciences* 54: 493–502. doi:10.1016/j.sbspro.2012.09.767.

Zafeiriou, E., G. Arabatzis, S. Tampakis, and K. Soutsas. 2014. “The Impact of Energy Prices on the Volatility of Ethanol Prices and the Role of Gasoline Emissions.” *Renewable and Sustainable Energy Reviews* 33: 87–95. doi:10.1016/j.rser.2014.02.001.

Zaghdoudi, T. 2018. “Asymmetric Responses of CO_2 Emissions to Oil Price Shocks in China: A Non-Linear ARDL Approach.” *Economics Bulletin* 38 (3): 1485–1493. http://www.accessecon.com/Pubs/EB/2018/Volume38/EB-18-V38-I3-P140.pdf.

Zeng, S., C. Jiang, C. Ma, and B. Su. 2018. “Investment Efficiency of the New Energy Industry in China.” *Energy Economics* 70: 536–544. doi:10.1016/j.eneco.2017.12.023.

Zhang, D., D. C. Broadstock, and H. Cao. 2014. “International Oil Shocks and Household Consumption in China.” *Energy Policy* 75: 146–156. doi:10.1016/j.enpol.2014.08.034.

Zhang, J., and L. Zhang. 2016. “Impacts on CO_2 Emission Allowance Prices in China: A Quantile Regression Analysis of the Shanghai Emission Trading Scheme.” *Sustainability* 8 (11): 1195. doi:10.3390/su8111195.

Zhang, W., and S. Yang. 2013. “The Influence of Energy Consumption of China on Its Real GDP from Aggregated and Disaggregated Viewpoints.” *Energy Policy* 57: 76–81. doi:10.1016/j.enpol.2012.10.023.

Zhang, Y. J. 2011. “The Impact of Financial Development on Carbon Emissions: An Empirical Analysis in China.” *Energy Policy* 39 (4): 2197–2203. doi:10.1016/j.enpol.2011.02.026.

Zhang, Y. J., Z. Liu, H. Zhang, and T. D. Tan. 2014. “The Impact of Economic Growth, Industrial Structure, and Urbanization on Carbon Emission Intensity in China.” *Natural Hazards* 73 (2): 579–595. doi:10.1007/s11069-014-1091-x.