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Asymmetric responses of CO2 emissions to oil price shocks in China: a non-linear ARDL approach

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Abstract

This paper investigates the asymmetric effects of oil price shocks on CO2 emissions in China using a nonlinear autoregressive distributed lags (NARDL) model. By performing the bounds test of the NARDL specification, we found a strong evidence of cointegration among variables, which include CO2 emissions, oil price, and economic growth. Results reveal the existence of nonlinear effects of oil price on CO2 emissions. Findings indicate also that oil price increases and decreases have significant short and long-run effects on CO2 emissions. This paper supports the view that in the long-run an oil price increase, raises CO2 emissions more rapidly than its decline in China.

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1 Introduction

Since 2014, China became the first energy consumer before the United States and the world's largest emitter of greenhouse gases since 2006. Its energy consumption has been multiplied by 2.5 since 2000 (from 1.5 MkWh to 3.8 MkWh) (Yearbook et al. (2017)).Coal is by far the primary source of primary energy (71% of consumption in 2014), followed by oil (18% in 2014), natural gas (5% in 2014), hydroelectricity (3%) and nuclear power (0.3% in 2014) (Yearbook et al. (2017)).Although China is the world's fifth-largest oil producer, China's crude oil imports accounted for 59.6% of its consumption in 2014 and more than quadrupled between 2000 and 2014 (70-308 million tonnes).Otherwise, Chinese coal production no longer covers the needs of the country since 2013, so in 2016 it imported 8.6% of its coal consumption.Finally, China imported 32.4% of its natural gas in 2014, although it is the world's 7th largest gas producer (Yearbook et al. (2017)).

However, the country's heavy dependence on foreign oil, environmental concerns related to the massive use of coal and the need to mitigate climate change have led China's energy strategy to diversify its energy use: gas and renewable energy, nuclear power being counted by the government among renewable, as well as better energy efficiency. In addition to being an economic leader, China has become a leader in international climate negotiations. While at the COP15 in Copenhagen in 2009, Chinese leaders had shown their reluctance to sign a binding agreement, it was at the same time that they began to reorient their national policy towards more environmental regulations and investment in green energy.

Nevertheless, since 2009 crude oil price reached its lowest level in 2015 at just under 50 $. This is largely due to the changing strategy of Organization of the Petroleum Exporting Countries(OPEC), the projected increase in Iran's exports, the contraction of world demand (especially emerging markets), the secular decline in oil consumption in the US and the emergence of oil substitutes. These phenomena, which are likely to persist suggesting a long-term low price scenario. This may reduce interest in renewable energy usage, increases fossil fuel consumption and CO2 emissions.

While, several empirical studies have been conducted on the relationship between CO2 emissions, oil price, and economic growth, relatively little attention has been given to the asymmetric long and short-run relationship between oil price and CO2 emissions.For instance, by employing the MESSAGE integrated assessment model,McCollum et al. (2016) studied the uncertainties that influencing the long-term impacts of oil price on energy markets and carbon emissions. Their results indicated sustained low or high oil price could have a major impact on the global energy system over the next several decades; and depending on how the fuel substitution dynamics play out, the carbon dioxide consequences could be significant. Chai et al. (2016) studied the impact of international oil price on energy conservation and emission reduction in China by using the Structural Vector Autoregression model (SVAR). Results show that, in the short term, the indirect influence of international oil price on energy consumption in China is relatively significant.By using the recently developed nonlinear autoregressive distributed lags (NARDL) model, Jammazi et al. (2015) examine the pass-through of changes in crude oil price, natural gas price, coal price and electricity price to the CO2 emission allowance price in the United States. Findings, indicated that the crude oil price has a long-run negative and asymmetric effect on the CO2 allowance price.Balaguer et al. (2014) estimated an environmental Kuznets curve dynamic structure for Spain over the period 1874-2011. Their results indicated that the rise in real oil price decreases CO2 emissions.By using a quantile regression framework,Hammoudeh et al. (2014) investigate the impact of changes in crude oil price, natural gas price, coal price, and electricity price on the distribution of the CO2 emission allowance price in the United States.Zhang and Cheng (2014) analyzed international oil price's impact on carbon emissions in China's transportation industry by using the partial least squares regression model. Results show that with the same GDP growth, the industry carbon emissions increase with the rise in international oil price, and vice versa, the industry carbon emissions decrease.Payne (2012) examined the causal dynamics between renewable energy consumption, real gross domestic product (GDP), carbon emissions, and real oil price in the United States using the Toda-Yamamoto long-causality test procedure over the period 1949 to 2009. Results show that real GDP, carbon emissions, and real oil prices did not have a causal impact on renewable energy consumption, unexpected shocks to real GDP and carbon emissions yielded a positive impact on renewable energy consumption over time. Van Ruijven and van Vuuren (2009) used the global energy model TIMER to explore the energy system impacts of exogenously forced low, medium and high hydrocarbon price scenarios, with and without climate policy. Their findings indicated without climate policy high hydrocarbon prices drive electricity production from natural gas to coal. Moreover, their results showed that in the transport sector, high hydrocarbon prices lead to the introduction of alternative fuels, especially biofuels and coal-based hydrogen which leads to increased emissions of CO2.

To the best of our acknowledge, the asymmetric relationship between oil price and CO2 emissions in China has not been previously studied. Thus, to fill this gap, we propose to investigate the positive and negative long and short-run impact of oil price on CO2 emissions for China. Different from previous studies, we use the nonlinear autoregressive distributed lags (NARDL) model developed by Shin et al. (2014) which allows potential long-run and short-run asymmetries in the oil price-CO2 emissions.

The rest of the paper is structured as follows. Section 2 presents the data and the model specification. Section 3 shows the model estimation and results and section 4 concludes.

2 Data and model specification

In this study, we use annual data of 37 observation for China. The period of the study spans from 1980 to 2016. All variables are collected from National Bureau of Statistics of China (Yearbook et al. (2017)), the U.S. Energy Information Administration, the Penn World Table (Feenstra et al. (2015)) and World Bank Development Indicators (WDI) database.

The dependent variable used in this study is the carbon dioxide emissions per capita (measured in metric ton per capita) as a proxy for greenhouse gas emissions. The explicative variables include crude oil price measured in U.S dollars per barrel of oil, coal consumption measured in Million tonnes oil equivalent and real GDP per capita measured in millions of constant 2010 U.S dollars.All variables are in natural logarithm and they meet the international standard definition.

To capture both long and short-run asymmetries effect of oil price on CO2 emissions, we apply the nonlinear ARDL model developed by Shin et al. (2014) . First, we specify the following asymmetric long-run equation of CO2 emissions:

$$lnCO2_t = \alpha_0 + \alpha_1 lny_t + \alpha_2 lop_t^+ + \alpha_3 lop_t^- + \varepsilon_t \tag{1}$$

Where $lnCO2_t$ refers to the natural logarithm of CO2 emissions and coal consumption, lny_t donate the natural logarithm of economic growth and $\alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_3)$ is a cointegrating vector or the vector of long run parameters to be estimated. From equation (1) and equation (2) lop_t^+ and lop_t^- are partial sums of positive and negative changes in lop_t (the natural logarithm of crude oil price):

$$lop_t^+ = \sum_{i=1}^{t} \Delta lop_t^+ = \sum_{i=1}^{t} max(\Delta lop_t, 0) \tag{2}$$

and

$$lop_t^- = \sum_{i=1}^{t} \Delta lop_t^- = \sum_{i=1}^{t} min(\Delta lop_t, 0) \tag{3}$$

From the above specification, α_2 donate the magnitude of the long-run relationship between positive shocks in oil price and CO2 emissions. However, α_3 capture the long-run relationship between negative shocks in oil price and CO2 emissions.

The long-run regression model can be written in an ARDL form as proposed by Pesaran and Shin (1998) and Pesaran et al. (2001) as:

$$lCO2_t = \beta_0 + \beta_1 lCO2_{t-1} + \beta_2 ly_{t-1} + \beta_3 lop^+_{t-1} + \beta_4 lop^-_{t-1} + \sum_{i=1}^{q} \rho_{1i} \Delta lCO2_{t-1} + \sum_{i=1}^{p} \rho_{2i} \Delta ly_{t-1} + \sum_{i=0}^{m} \rho_{3i} \Delta lop^+_t + \sum_{i=0}^{n} \rho_{4i} \Delta lop^-_t + \mu_t \tag{4}$$

Where all variables are as defined above, p, q, m and n are lag orders.β_0 and β_1, represent the constant term and the lagged dependent variable parameter.β_3 and β_4 the parameters of the partial sums of positive and negative changes in lop_t. $\alpha_2 = \frac{-\beta_3}{\beta_1}$ and $\alpha_3 = \frac{-\beta_4}{\beta_1}$, represent the long-run impact of positive and negative oil price changes on CO2 emissions. $\sum_{i=0}^{m} \rho_{3i}$ measured the short run impact of positive oil price changes on CO2 emissions and $\sum_{i=0}^{n} \rho_{4i}$ measured the short run effect of negative changes in oil price on CO2 emissions. $\sum_{i=0}^{m} \rho_{1i}$ and $\sum_{i=0}^{m} \rho_{2i}$, measured the short run effect of the lagged and differenced dependent variable and the GDP per capita on CO2 emissions. μ_t, represents the error term. By applying NARDL approach we can capture asymmetries in the relationship between oil price and CO2 emissions in both long and short-run.

The econometric approach is based on four steps. In the first one, the stationarity of each variable is examined by performing two unit roots tests, namely, Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test. In the second one, if the variables are found to have different order of integration I(0) and I(1), we estimate equation (4) using the ordinary least squares (OLS) method, and the lag length is chosen based on the information criterion SIC or general-to-specific. In the third one, we perform a test for the presence of cointegration among the variables using a bounds testing approach of Pesaran et al. (2001) and Shin et al. (2014).Finlay, with the presence of cointegration, we estimate the long-run asymmetric impact of oil price on CO2 emissions and we also drive the asymmetric cumulative dynamic multiplier effects m_h^+ and m_h^+, the first one is associated with the change (a one percent change) in lop_t^+ and the second one is associated with the change (a one percent change) in lop_t^-:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial lCO2_{t+j}}{\partial lop^+_{t-1}}, \ m_h^- = \sum_{j=0}^{h} \frac{\partial lnCO2_{t+j}}{\partial lop^-_{t-1}} \ j = 0, 1, 2, ... \tag{5}$$

Note that as $h \longrightarrow \infty$, $m_h^+ \longrightarrow \alpha_2 \ and \ m_h^- \longrightarrow \alpha_3$

3 Model estimation and results

3.1 Unit root tests

Results of unit root tests are reported in Table 1. From this table it can be noted that the null hypothesis of the unit root cannot be rejected at the 1% level of significance for all time series taken in level. However, by testing for the unit root in the first difference, all unit root tests reject the null hypothesis at the 1% and 5% level of significance except lcoal.

Table 1: Unit root test

	Level		First difference	
Variable	ADF	PP	ADF	PP
lCO2	-0.247372	0.868017	-3.173470**	-3.173470**
lop	-1.132276	-1.115603	-5.513460***	-5.509609***
ly	-0.471866	-0.123068	-4.228711**	-3.444835**
lcoal	-1.592797	-0.747656	-4.9965***	-

Notes: ***, **, * indicate statistical significance at 1, 5 and 10 percent level of significance, respectively.

Results of unit roots with structural break reported in Table 2 indicate that the null hypothesis of the unit root tests with break point cannot be rejected at the 1% and 5% level of significance for all time series taken in level except lco2. However, by testing for the unit root in the first difference, the unit root test rejects the null hypothesis at the 1% and 5% level of significance for all time series.

Table 2: Zivot-Andrews Unit Root Test

Variable	Z&A test for level		Z&A test for 1st difference	
	Statistics	TB	Statistics	TB
lCO2	-4.046091**	2002	-4.179315***	2000
lop	-3.773667	2003	-6.162170**	2014
ly	-1.557232	2002	-4.476339 **	2007
lcoal	-4.996550	2002	-3.183018**	2011

Notes: ***, **, * indicate statistical significance at 1, 5 and 10 percent level of significance, respectively.

3.2 Cointegration test

The time series unit root tests ADF, PP and break point ADF confirm that all variables are integrated in order I(1) and no I(2) variables are involved except coal consumption with I(2) which is not introduced into the model, then we perform the cointegration test for nonlinear specifications. The results of the bounds test reported in Table 3 provide strong evidence for cointegration among the variables.

Table 3: Bounds tests for non-linear cointegration

Model specification	F-Statistics	95% lower bound	95% upper bound	Conclusion
nonlinear	10.0371	6.183	7.873	Cointegration

Notes: the critical values are from Narayan (2005) case III 1% significance level.

3.3 NARDL

Given the evidence of cointegration among variables, we perform the NARDL approach.The results of the NARDL estimation are reported in Table 4.

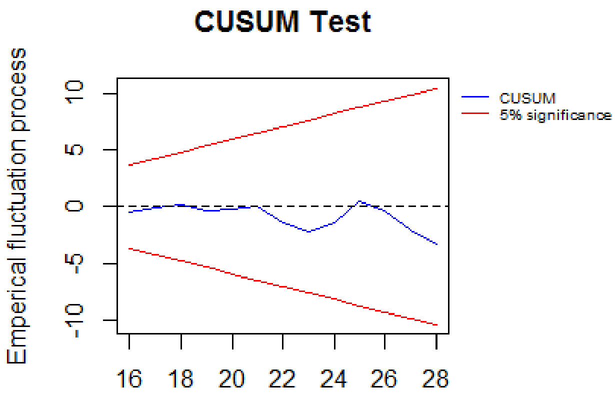
Table 4: Nonlinear ARDL estimation results

Variable	Coefficients	Prob	
Const	0.5294	0.0134	*
lco2_1	-0.5209	0.0000	***
lop^{+}_1	0.2576	0.0000	***
lop^{-}_1	-0.1173	0.0172	*
D.lco2_1	0.5106	0.0014	**
D.lco2_2	0.1980	0.1908	
D.lco2_3	0.1633	0.2665	
$D.lop^{+}$_1	-0.1882	0.0041	**
$D.lop^{+}$_2	-0.2502	0.0004	***
$D.lop^{+}$_3	0.0102	0.8553	
$D.lop^{-}$_1	0.0044	0.9146	
$D.lop^{-}$_2	0.0376	0.3932	
$D.lop^{-}$_3	-0.0162	0.6796	
ly_1	-0.1680	0.0414	*
D.ly_1	0.7309	0.0283	*
D.ly_2	-0.7312	0.0476	*
D.ly_3	1.1936	0.0019	**
R^2	0.9251	-	
J-B	0.7564	0.6850	
LM	10.4735	0.2224	
ARCH(3)	1.0412	0.7912	

Notes: J-B is the Jarque-Bera test for error normally, LM the test for error autocorrelation, and ARCH(.) is the ARCH test for autoregressive conditional heteroskedasticity up to the lag order given in the parenthesis.
***, **, * indicate statistical significance at 1, 5 and 10 percent level of significance, respectively.

According to Jarque-Bera test for error normality (J-B), the error tends to follow normal distribution. Moreover, the serial correlation LM test reveals the absence of autocorrelation in the residuals.Besides, the autoregressive conditional heteroskedasticity ARCH shows that the residuals have constant variance over time. Furthermore, the CUSUM and CUSUM of squares tests represented in Figure 1 and Figure 2, reveal the stability of the model coefficients since the estimated model lies within the 5% significance line for CUSUM and CUSUM of squares tests.

The short-run estimation results show that a 1% increase in oil price increases CO2 emissions by 25%. However, findings indicate that a 1% decrease in oil price decreases CO2 emissions by 11%. Hence, in the short-run any increase in oil price will raise carbon dioxide emissions faster then decreases them.



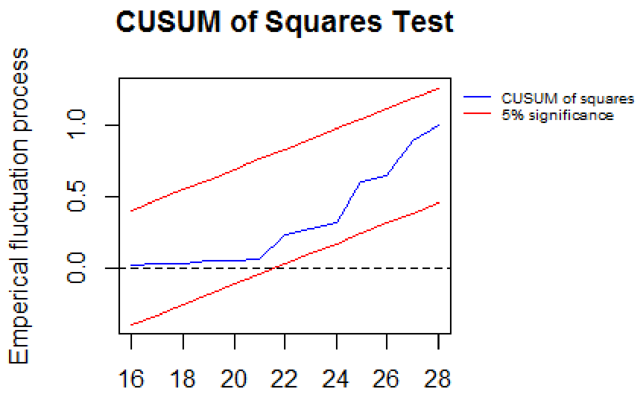


Figure 1: CUSUM test (Model 1)

Figure 2: CUSUM of squares test (Model 1)

The long run coefficients computed from the dynamic model shown in Table 4 are reported in Table 5.

Table 5: Long-run relations

Variable	Coefficients	Prob	
lop^{+}_1	0.4946	0.0000	***
lop^{-}_1	-0.2253	0.0000	***
D.lco2_1	0.9802	0.0000	***
D.lco2_2	0.3802	0.0000	***
D.lco2_3	0.3136	0.0000	***
$D.lop^{+}\_1$	-0.3614	0.0000	***
$D.lop^{+}\_2$	-0.4803	0.0000	***
$D.lop^{+}\_3$	0.0196	0.5119	
$D.lop^{-}\_1$	0.0084	0.6858	
$D.lop^{-}\_2$	0.0723	0.0073	**
$D.lop^{-}\_3$	-0.0311	0.1036	
ly_1	-0.3225	0.0000	***
D.ly_1	1.4031	0.0000	***
D.ly_2	-1.4036	0.0000	***
D.ly_3	2.2912	0.0000	***
Long Run Asymmety test			
F-stat: 24.8701		Pvalue: 0.0002	

Notes: ***, **, * indicate statistical significance at 1, 5 and 10 percent level of significance, respectively.

The long-run estimation results show that all coefficient except $D.lop^{-}\_1$ are significant at 1% and 5% significance level and they can be interpreted as elasticity estimates. Moreover, the long-run asymmetry result shows the acceptance of the alternative hypothesis, in the long run, implying that CO2 emissions respond differently to a decrease as compared to an increase in oil price. In particular, the value of the Wald test is equal to 24.87 and statistically significant at 1% level. Results indicate also that a 1% increase in economic growth decreases CO2 emissions by 32%. This means that the share of non-renewable energy in the production of goods and services has decreased. In 2015, coal generated less than 70% of Chinese electricity, 10% points less than four years ago (in 2011).Indeed, by supporting investments in more efficient and cleaner energies, China accelerated their renewable roll-out and have set voluntary targets for the reduction of CO2 emissions by 58% in 2020 Agency (2016).

However, the asymmetric long-run relationship between oil price and CO2 emissions with the increase in oil price is significant. Results suggest that a 1% increase in oil price increases CO2 emissions by 49%.Nevertheless, the negative change in oil price is found to be negative and significant. Therefore, a 1% increase in oil price decreases CO2 emissions by 22%. Consequently, the positive effect exceeds the negative effects. Its well knew that industries in China are quite dependent on coal (71% of total energy consumption in 2014) which represents the most polluting fossil energy (oil 18% in 2014). Thus, any increases in oil price may lead to a reduction in oil importation and increase coal energy consumption the only fossil resource that China has in abundance and consequently raise CO2 emissions. The industrial sector is the most coal energy consumer with 37.565 Million tonnes in 2017 compared to transport, storage and post with 0.0878 Million tonnes (Yearbook et al. (2017))

In order to identify the fossil fuel substitution possibilities, we apply the Choi et al. (1997) canonical cointegration regression (CCR) with both I(1) and I(2) variables to the following equation:

$$lop_t = \lambda_0 + \lambda_1 lcoal_t + \mu_t \tag{6}$$

Where lop_t refers to the natural logarithm of oil price (I(1),Table 1), $lcoal_t$ donate the natural logarithm of coal consumption (I(2),Table 1), $\lambda = (\lambda_0, \lambda_1)$ is the vector of long run parameters to be estimated and μ_t is the error term.

The estimated results from CCR estimates, reported in Table 6 indicate that a 1% increase in oil price increases coal energy consumption by 112%. This findings show clear prospects for fuel substitution. These results further the argument that fuel substitution from oil to coal energy would higher pollution.

Table 6: Canonical cointegration regression (CCR)

Variable	Coefficients	Prob	
lop	1.129844	0.000	***
cons	1.188575	0.000	***
R-squared		0.557916	

Notes: ***, **, * indicate statistical significance at 1, 5 and 10 percent level of significance, respectively.

Figure 3 reports the cumulative dynamic multipliers of 1% oil price increase and a decrease in CO2 emissions. We can observe that increases in oil price takes about 6 to 7 years to impact CO2 emissions and converges to the long run coefficient 0.4946. However, the cumulative negative effect of a decrease in oil price on CO2 emissions does not disappear after 30 years.

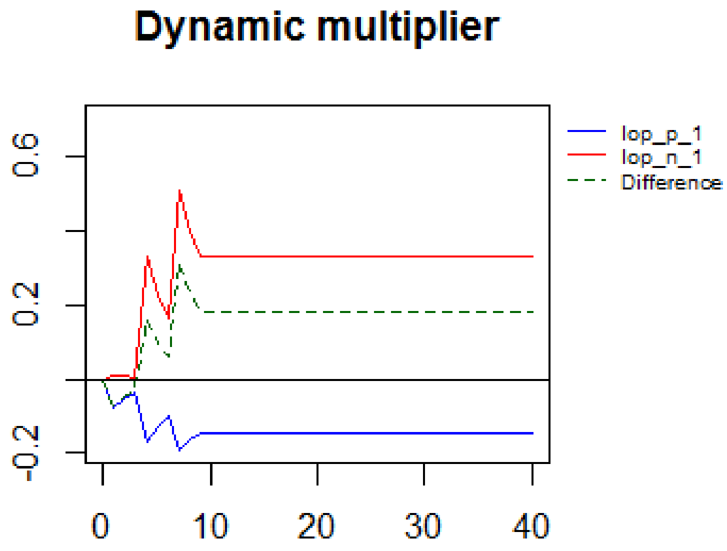


Figure 3: Dynamic multiplier

4 Conclusion

This paper explores the relationship between oil price and CO2 emissions in China over the period 1980-2016. Results from the nonlinear autoregressive distributed lags (NARDL) model estimates indicate that the nexus between oil price and CO2 emissions is asymmetric. Moreover, findings show that oil price increase and decrease have significant short and long-run effects on CO2 emissions.

The findings of this study assert that oil price increases CO2 emissions more rapidly than its decline. Thus, productions of goods and services in China still dependent on oil energy use. Moreover, as a reaction to oil price volatility, oil is substituted by coal which is abundant in China. Nevertheless, in November 2014, the United States and China issued a joint statement committing to increasing the share of "new energy" (renewable and nuclear energy) to 15% of the energy mix in 2020 (of which 5% 20% by 2030). The 12th Five-Year Plan (2011-2015) sets a target of 16% reduction in energy intensity and introduces for the first time in a five-year plan a reduction target of (CO2 emissions per unit of GDP) set at 17%. These targets are expected to be achieved, with China's economic growth shifting to less carbon-intensive sectors.

This paper has some relevant policy implications. To guide the speculative behavior of market players towards the goal of supply-demand equilibrium, oil price formation mechanism should be refined and more rationalized. However, China can enhance energy saving and reduce pollution by linking its market to the international oil price system where the can be correctly reflected to motivate spontaneous renewable energy use. In addition, to mitigate pollution, the biggest polluters have to decrease energy intensity, increase energy efficiency and renewable energy use. Governments need to promote renewable energy generation and support investments in more efficient and cleaner energies.

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