Clean energy consumption and CO2 emissions: Does China reduce some pollution burdens through environmental regulation?

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Abstract

This study scrutinizes the asymmetry phenomenon in environmental regulation- clean energy and environmental quality nexus in China. The study adopts the time series nonlinear ARDL approach proposed by Shin et al. (2014), which separates positive shocks from negative shocks to environmental regulation. Our findings reveal that there is evidence of asymmetry in the environmental regulation- clean energy nexus in China in the short and long run, while asymmetry holds in direction and magnitude in short-run and only in magnitude in long run over the period of study. We find that the response of environmental quality to environmental regulation shocks differs in magnitude and direction in the only long run. The asymmetries exist in clean consumption and CO2 emissions findings, Thus China should revise the policies of energy and environment.

Keywords: Environmental regulation. Clean energy. Environmental quality. China.

Introduction

Environmental issues are attracting worldwide attention as climate change and environmental degradation are increasingly disrupting ecosystems including human life. Preserving environmental quality without sacrificing economic performance has become the key concern all over the world. Mainly emerging countries face the issue of sustaining their growth and the environment simultaneously. Against this backdrop, China is not properly managing economic growth, clean energy, and the environment. The growth of the Chinese economy largely depends upon its increasing industrialization which is the key cause of high pollution as well. Meanwhile controlling environmental pressure has become a worldwide agenda. The United Nations

(UN) sustainable development goals (SDGs) have more focus on the environment. SDG 13 is particularly focusing on climate action. China is a fast-growing polluting economy and contributed around 28.8 percent to global CO_2 emissions (BP Report 2020). Lately, China has approved an "environmental protection tax law in 2018", to limit pollution emissions (Jia 2018). While pursuing SDGs, China needs to increase its environmental regulations and their implementations (Chen et al. 2018; Hao et al. 2018; Wu et al. 2020).

Exploring the nexus among environmental regulation, energy use, and CO_2 emissions is useful from different viewpoints. The results help to better reforms and management of environmental taxes, price controls, energy sector issues, sectoral energy policies, and environmental management at the country and global level. The role of environmental regulation is critical for the energy sector in the following manners. First, environmental taxes increase the cost of conventional sources of energy, and demand for alternative clean energy sources tends to increase. Second, carbon taxes set a certain constraint on emission trading, and, contrary to this no limit is set on emissions price (Chiu et al. 2015). In a recent study, Shahzad (2020) reviews the literature up to 2020 to explore relationships between environmental tax, energy demand, and environmental pollution. Shahzad (2020) concludes that the extant literature provides ambiguous findings and requires a more comprehensive study. These facts inspire us to explore the dynamics of the applications of environmental regulation taxes on clean energy demand and CO_2 emissions.

The link between environmental regulation and carbon emissions has attracted worldwide attention in recent decades. Standard literature, however, suggests controversial findings. The earlier studies were of the strong view that environmental regulation can help to control environmental pollution (Porter & Van der Linde 1995; Laplante & Rilstone; 1996; Marconi 2012; Cairns 2014). In this regard, Porter's hypothesis suggests that strict environmental laws force firms to innovate eco-friendly production methods, thereby alleviating the environmental burden. This hypothesis is suggested by Porter and Van der Linde (1995) who assert that stringent environmental regulations can invigorate corporate innovation endeavors. Meanwhile, the subsequent "compensation effect" can partly or even entirely compensate the cost of environmental regulation, contributing to productivity.

Laplante and Rilstone (1996), showed favorable negative impacts of environmental regulation on pollution emissions in Canada. Likewise, Marconi (2012) analyzed the outcome of environmental regulations for China and EU 14. Their findings also confirm that regulations can mitigate emissions. Van der Ploeg and Withagen (2012), claimed that environmental regulation can have favorable effects on carbon reduction and green welfare. Likewise, Cairns (2014) also showed that found that environmental regulation helps to manage carbon emissions.

Meanwhile, a group of scholars doubted the favorable role of environmental regulation for emissions abatement (Sinn 2008; Smulders et al. 2012; Ritter & Schopf 2014). They argued that regulation may not mitigate pollution, generally referred as the "green paradox" hypothesis. Sinn (2008) views that environmental regulation is positively associated with CO_2 emissions. He believes that carbon tax takes time to be implemented and meanwhile CO_2 emissions escalate. Similarly, research by Smulders et al. (2012) demonstrated that the premature information of environmental regulations fosters CO_2 emissions. Similarly, Ritter and Schopf (2014) demonstrated that "green policy" fosters the mining of fossil fuels and enhances CO_2 emissions.

Some scholars consider that the “green paradox” and “emission reduction effect” of environmental regulation work at the same time (Zhang et al. 2020; Min 2018). In this regard, Min (2018) showed that initially regulations support “green paradox” but after a certain threshold point “emission reduction effect” begins to dominate. Thus, an inverted U-shaped phenomenon is likely to take place. Similarly, employing the panel data of 30 regions in China and the threshold regression model, Zhang et al. (2020) validated an inverted U-shaped association between environmental regulation and CO2 emissions. Empirical research is growing in this field. One group of the studies focused on “enterprise-level” evidence. For example, Gamper-Rabindran and Finger (2013) employed the panel data of 1759 enterprises over the period 1988 to 2001 and explore the environmental impact of self-regulation for enterprises that joined the “responsible care” alliance. Surprisingly, their results show that regulation has emissions escalating effect. The authors suggest the likely reason could be the absence of the certification by a third party. Contrary to this, Khanna and Kumar (2011) showed that high-intensity regulation improves environmental efficiency for enterprises.

One group of studies has revealed mixed effects of environmental regulation on carbon emissions in China (Chen et al. 2018; Hao et al. 2018; Wu et al. 2020). Chen et al. (2018) explored the regulation and environmental nexus in the presence of informal economy for 30 provinces of China from 1998 to 2012. Their findings show mixed results. On the one hand, their estimates show that both shadow economy and stringent environmental regulation enhance CO2 emissions in China. On the other hand, they show that regulation can help to control pollution depending upon a given level of the shadow economy.

Similarly, Hao et al. (2018) investigate the impact of environmental regulations on environmental quality employing panel data of Chinese cities from 2003 to 2010. They use the first difference GMM to estimate the model. The results do not confirm the environmental improving effect of the regulations. However, the combined effect of FDI and the environmental regulation turns out to be negative and significant suggesting the importance of FDI in achieving the benefit of environmental regulations. In the same manner, using the data for 30 provinces of China over the period 2006-2015 and the GMM approach of estimation, Wu et al. (2020) also found mixed evidence of environmental regulation and environmental quality nexus. Environmental regulation curbs emissions in central and eastern China while it did not curb emissions in the western region of China.

The key objective of the present study is to investigate the role of environmental regulation in clean energy and the environment in China from 1993 to 2019. This research is particularly main for the policy perspective because environmental regulation requires scientific evidence. Even though the new research work provides valuable insights on regulation, clean energy, and emissions, however, we could not find any famous study for China that has explored the asymmetric role of environmental regulation for clean energy and carbon emissions. Therefore more research is required to provide new and more conclusive outcomes. The prior empirical studies mainly focus on the evidence-based firm-level experience, city, or region-specific studies. The findings of these studies cannot be generalized at an aggregate level for China. Besides, the existing studies assume linear relationships which can lead to misleading results.

Section 2 describes the “methodology and model”. The “empirical results and discussion” are reported in Section 3. Finally, section 4 provides a “conclusion and suggests policy implications”.

Model and method

In formulating the clean energy consumption and carbon emissions models, we follow the literature, e.g., Wang and Shen (2016) and Wang et al. (2019) by assuming that environmental regulation is the main determinant of clean energy and environmental quality. As such we showed equations (1 and 2) are below as:

$$CEC_t = \rho_0 + \rho_1 ER_t + \rho_2 EM_t + \rho_3 ET_t + \rho_4 GDP_t + \rho_5 FDI_t + \varepsilon_t \qquad (1)$$

$$CO_{2,t} = \rho_0 + \rho_1 ER_t + \rho_2 EM_t + \rho_3 ET_t + \rho_4 GDP_t + \rho_5 FDI_t + \varepsilon_t \qquad (2)$$

Equation (1) is the China clean energy consumption and equation (2) is the environmental quality model and assumed to rely on the level of environmental regulation denoted by ER. Since increased environmental regulation leads to more clean energy consumption, we expect estimates of ρ_1 in equation (1) to be positive, while environmental regulation leads to more environmental quality; we expect estimates of ρ_1 in equation (2) to be negative. Equations (1 & 2) provide the long-run estimates only; however, we are concerned with both short-run and long-run estimates. To that end, we need to reconsider the above equation in the error correction format as displayed below:

$$\Delta CEC_t = \beta_0 + \sum_{k=1}^{n} \beta_{1k} \Delta CEC_{t-k} + \sum_{k=0}^{n} \beta_{2k} \Delta ER_{t-k} + \sum_{k=0}^{n} \beta_{3k} \Delta EM_{t-k} + \sum_{k=0}^{n} \beta_{4k} ET_{t-k} + \sum_{k=0}^{n} \beta_{5k} GDP_{t-k} + \sum_{k=0}^{n} \beta_{6k} FDI_{t-k} + \rho_1 CEC_{t-1} + \rho_2 ER_{t-1} + \rho_3 EM_{t-1} + \rho_4 ET_{t-1} + \rho_5 GDP_{t-1} + \rho_6 FDI_{t-1} + \varepsilon_t \qquad (3)$$

$$\Delta CO_{2,t} = \beta_0 + \sum_{k=1}^{n} \beta_{1k} \Delta CEC_{t-k} + \sum_{k=0}^{n} \beta_{2k} \Delta ER_{t-k} + \sum_{k=0}^{n} \beta_{3k} \Delta EM_{t-k} + \sum_{k=0}^{n} \beta_{4k} ET_{t-k} + \sum_{k=0}^{n} \beta_{5k} GDP_{t-k} + \sum_{k=0}^{n} \beta_{6k} FDI_{t-k} + \rho_1 CO_{2,t-1} + \rho_2 ER_{t-1} + \rho_3 EM_{t-1} + \rho_4 ET_{t-1} + \rho_5 GDP_{t-1} + \rho_6 FDI_{t-1} + \varepsilon_t \qquad (4)$$

Specifications (3 & 4) have occupied the form of the linear ARDL of Pesaran et al. (2001). Once we estimate equations (3 & 4), we get both long-run with short-run estimates simultaneously. The estimates connected to the first-difference indicators (Δ) represent the short-run estimates; whereas, the estimates connected to ρ_2- ρ_6 normalized on ρ_1 are long-run. Moreover, this method is efficient in a small sample size. Another advantage is that pre-unit root testing is not a prerequisite for ARDL. This method provides robust estimates even as the variables are incorporated by distinct orders such as I(0) otherwise I(1). But we cannot include any variable, which is I(2). Shin et al. (2014) transform the above approach so that we can also examine the possibility of asymmetries, which contain positive changes in environmental regulation as well as negative changes. The mathematical form of the partial sum procedure is presented below:

$$ER^{+}{}_t = \sum_{n=1}^{t} \Delta ER^{+}{}_t = \sum_{n=1}^{t} \max\left(\Delta ER^{+}{}_t, 0\right) \qquad (5)$$

$$ER^{-}{}_t = \sum_{n=1}^{t} \Delta ER^{-}{}_t = \sum_{n=1}^{t} \min\left(\Delta ER^{-}{}_t, 0\right) \qquad (6)$$

In equation (5), ER^+ represents the positive changes in the series, whereas equation (6) ER^- represents the negative changes in the selected series. Next, we incorporate partial sum variables in original models as shown below:

$$\Delta CEC_t = \beta_0 + \sum_{k=1}^{n} \beta_{1k} \Delta CEC_{t-k} + \sum_{k=0}^{n} \beta_{2k} \Delta {ER^+}_{t-k} + \sum_{k=0}^{n} \beta_{3k} \Delta {ER^-}_{t-k} + \sum_{k=0}^{n} \beta_{4k} \Delta EM_{t-k} + \sum_{k=0}^{n} \beta_{5k} ET_{t-k}$$

$$+ \sum_{k=0}^{n} \beta_{6k} GDP_{t-k} + \sum_{k=0}^{n} \beta_{7k} FDI_{t-k} + \rho_1 CEC_{t-1} + \rho_2 {ER^+}_{t-1} + \rho_3 {ER^-}_{t-1} + \rho_4 EM_{t-1}$$

$$+ \rho_5 ET_{t-1} + \rho_6 GDP_{t-1} + \rho_7 FDI_{t-1} + \varepsilon_t \qquad (7)$$

$$\Delta CO_{2,t} = \alpha_0 + \sum_{k=1}^{n} \beta_{1k} \Delta CO_{2,t-k} + \sum_{k=0}^{n} \beta_{2k} \Delta {ER^+}_{t-k} + \sum_{k=0}^{n} \beta_{3k} \Delta {ER^-}_{t-k} + \sum_{k=0}^{n} \beta_{4k} \Delta EM_{t-k} + \sum_{k=0}^{n} \beta_{5k} ET_{t-k}$$

$$+ \sum_{k=0}^{n} \beta_{6k} GDP_{t-k} + \sum_{k=0}^{n} \beta_{7k} FDI_{t-k} + \rho_1 CO_{2,t-1} + \rho_2 {ER^+}_{t-1} + \rho_3 {ER^-}_{t-1} + \rho_4 EM_{t-1}$$

$$+ \rho_5 ET_{t-1} + \rho_6 GDP_{t-1} + \rho_7 FDI_{t-1} + \varepsilon_t \qquad (8)$$

After entering the partial sum variables in place of original variables, the new equations (7 & 8) are known as the NARDL of Shin et al. (2014), which is a new form of the ARDL model. This method is subject to the same cointegration test and critical values as Pesaran et al. (2001) proposed for the linear ARDL model. However, few asymmetric tests are to be applied to confirm the presence of asymmetry in the impacts of positive and negative components of ER. First, we see if the size of the estimate attached to ΔER^+ at a particular lag is different from the size of the estimate attached to ΔER^- or not, and if they are different this is a sign of short asymmetry. Then, to confirm the short-run asymmetries, we nullified the null hypothesis of Wald-SR, i.e., $\sum\beta_{2k} = \sum\beta_{3k}$. Finally, the long asymmetries will confirm if we nullified the null hypothesis of Wald-LR i.e. $\frac{\rho_2}{-\rho_1} = \frac{\rho_3}{-\rho_1}$.

The data are attained from the IMF and World Bank by covering the period 1993–2019. Annual data of China is employed for analysis and we used the consumption of clean energy and CO2 emissions as dependent variables. We used the electric power consumption (kWh per capita) and carbon dioxide emissions (kilotons) as proxies of clean energy demand and environmental quality (Usman et al. 2020). The remaining details of independent and control variables are also given in Table 1. We transformed CO2, clean energy consumption, environmental technology, and GDP per capita into logarithmic form.

Table I: Definitions and sources

Variables	Abbreviations	Definitions
Carbon dioxide emissions	CO2	Carbon dioxide emissions (kilotons)
Clean energy consumption	CEC	Electric power consumption (kWh per capita)
Environmental regulation	ER	Environmentally related taxes, % total tax revenue
Environmental monitoring	EM	Total number of environmental monitoring

Environmental technology	ET	Environment-related technologies
GDP per capita	GDP	GDP per capita (constant 2010)
Financial development index	FDI	An index that captures financial markets development.

Results and discussion

The first is used without and with structural breaks unit root tests to observe the order of integration of all nominated variables. The results are provided in Table 2 and the turns out depict mixed order of integration, but none of the variables is integrated I (2). This section also reports the empirical results and their discussion. The long and short-run results are obtained using ARDL method employing time series data for China. Two models are estimated where the first model provided the estimates for clean energy and the second model provided the outcomes for the CO2 emissions model. Table 3 presents the empirical outcomes using linear ARDL model specification whereas Table 4 shows results based on nonlinear ARDL model specification. As discussed earlier, the main objective of the present study is to explore the dynamic linear and nonlinear effects of environmental regulation on clean energy and CO2 emissions.

Table 2: Without and with structural breaks unit root test

	without structural breaks unit root test			with structural breaks unit root test				
	I(0)	**I(1)**	**Decision**	**I(0)**	**Break period**	**I(0)**	**Break period**	**Decision**
CO2	-0.535	-3.090**	I(1)	-4.562**	2002			I(0)
CEC	-1.595	-3.712**	I(1)	-3.212	2002	-9.235***	2015	I(1)
ER	-1.632	-3.861**	I(1)	-2.012	2010	-11.20***	2013	I(1)
EM	-3.431		I(0)	-6.235***	2009			I(0)
ET	-1.217	-2.762*	I(1)	-2.032	2003	-5.236***	2018	I(1)
GDP	-2.268*		I(0)	-6.565***	2004			I(0)
FDI	-2.732*		I(0)	-3.012	2003	-7.653***	2009	I(1)

In Table 3, the parameter estimate of ER has a positive and statistically significant effect on clean energy consumption at a 10% level of significance in the short-run, implying that ER helps to mitigate carbon emissions in the short-run. Particularly, the numerical estimate suggests that a one percent increase in environmental regulation will increase demand for clean energy consumption by 0.042% in the short run. The estimates for EM and ET suggest that no significant relationship is turned out between EM/ET and clean energy consumption suggesting that it is environmental regulation that mainly regulates the demand for clean energy in the short run. Similarly, FDI did not show any significant effect on clean energy in the short run. The effect of GDP, however, is positive in the short run suggesting that a 1% increase in economic growth will escalate the demand for clean energy in China by 2.396%.

Panel B of Table 3 presents the long-term result based on the linear model. The parameter estimate of ER has a positive significant influence on energy consumption in the long run as well. Particularly, a one percent increase in ER will mitigate carbon emissions by 0.117%. Thus the effect of ER is not only consistent, but the magnitude of effect also increases by almost three-time implying that environmental regulation has more impact in the long run. Interestingly, the effects of EM and ET turn out to be positive and significant in the long run revealing that EM and ET have more power to influence clean energy in the long run. The coefficient of EM (ET) reveals that a 1 % increase in EM (ET) will increase the demand for clean energy by 0.088 % (0.376 %) in the long run. The impact of GDP, however, turns out to be insignificant in the long run. The role of FDI also remains insignificant in the long run.

The third and bottom panel of Table 3 presents the results of numerous diagnostic tests. The estimates of “the Lagrange multiplier (LM) test” are statistically insignificant signifying that the residuals are free from autocorrelation problem. Some other diagnostic tests including “Ramsey RESET test, Heteroskedasticity test, and CUSUM test” are also applied. The numerical values of the RESET test are insignificant implying that functional forms are not mis-specified, and our selected models are suitable. In addition, the numerical value of the BP test is also insignificant showing that the Heteroskedasticity problem does not influence the outcomes. Finally, to test for the stability of linear ARDL models “CUSUM and CUSUM-squared tests” are applied where “S” shows the stable model and the “US” denotes the unstable model. Both models are shown to be stable in the estimation linear ARDL. Besides the test for goodness of fit also shows a high level of goodness of fit. Thus, with these tests' outcomes, we can safely conclude that our empirical results based on the linear ARDL are efficient and stable.

The results for the CO2 model suggest that the effect of EM on CO2 emissions is negative and significant in the short run. Particularly a 1 % increase in EM will mitigate CO2 emissions by 0.033 percent in the short run. The effects of EM and ET do not show any significant impact on CO2 emissions in the short run. Similarly, GDP is not significantly associated with CO2 emissions in the short run. The effect of FDI, however, is positive and significant at a one percent level of significance in the short run. The numerical value of FDI suggests that a one percent increase in FDI will control emissions by 0.972 percent in the short run. Thus financial development helps to improve environmental quality in the short run.

Panel B of Table 3 presents the long-run result based on the linear model. The parameter estimate of ER has a negative and significant influence on CO2 emissions in the long run as well. Particularly, a one percent increase in ER will mitigate carbon emissions by 0.142 percent. Thus the effect of ER is not only consistent, but the magnitude of effect also increases by almost four times in the long run. This result is backed by prior studies (Porter & Van der Linde 1995; Laplante & Rilstone; 1996; Marconi 2012; Cairns 2014). The effect of EM remains insignificant in the long run as well, however, the effect of ET turns out to be negative and significant in the long run revealing ET has more power to influence CO2 emissions in the long run. The coefficient of ET reveals that a one percent increase in ET will decrease CO2 emissions by 2.085 % in the long run. The impact of GDP, surprisingly, turns out to be significant with a negative sign in the long run. The numerical value suggests that a one percent increase in GDP will decrease emissions by 3.687 percent in the long run. This finding suggests that in the long-run economic growth can help to lower the emissions owing to the reasons of replacement of fossil fuels with clean energy and promoting environmental care in the long run. The role of FDI also remains significant with a negative sign suggesting that FDI can play a key role in the mitigation of CO2 emissions in the long run. Further, the magnitude of the effect is also increased in the long run.

Table 3: ARDL estimates of clean energy and CO2

	Clean energy				CO2			
Variable	**Coefficient**	**S.E**	**t-Stat**	**Prob.**	**Coefficient**	**S.E**	**t-Stat**	**Prob.**
Short run								
D(ER)	0.042***	0.009	4.585	0.003	-0.033**	0.014	2.339	0.048
D(ER(-1))	-0.151***	0.012	12.94	0.000				
D(EM)	0.021	0.027	0.789	0.456	0.032	0.041	0.777	0.459
D(EM(-1))	0.031	0.032	0.960	0.369	0.115*	0.067	1.726	0.123
D(ET)	-0.016	0.089	0.181	0.861	0.148	0.125	1.183	0.271
D(ET(-1))	-0.146	0.118	1.237	0.256	-0.793***	0.258	3.070	0.015
D(GDP)	2.396***	0.464	5.167	0.001	0.114	0.828	0.137	0.894
D(GDP(-1))	0.667	0.488	1.366	0.214	1.992***	0.708	2.814	0.023
D(FDI)	0.451	0.373	1.211	0.265	-0.972*	0.508	1.912	0.092
D(FDI(-1))	-0.271	0.227	1.192	0.272	0.469	0.329	1.423	0.192
Long run								
ER	0.117***	0.008	14.36	0.000	-0.142***	0.044	3.211	0.012
EM	0.088**	0.041	2.162	0.067	-0.019	0.078	0.247	0.811
ET	0.376***	0.129	2.915	0.023	-2.085***	0.800	2.607	0.031
GDP	-0.061	0.265	0.229	0.825	-3.687**	1.769	2.084	0.071
FDI	1.223	0.859	1.424	0.197	-4.651**	1.965	2.367	0.046
C	3.173***	0.897	3.538	0.010	27.69***	7.217	3.837	0.005
Diagnostic								
F test	8.023***				8.497***			
ECM(-1)	-0.872***	0.055	15.71	0.000	-0.469	0.148	3.161	0.013
LM	2.370				0.922			
BP	0.454				0.508			
RESET	2.465				1.577			
CUSUM	S				S			
CUSUM-sq	S				S			

Note: *p<0.1, **p<0.05, and ***p<0.01

The ongoing analysis revolves around a question: "How do the results change if we apply the nonlinear ARDL model?" To check whether or not the effect of environmental regulation, environmental monitoring and environmental technology on clean energy consumption, and CO2 emission is nonlinear or not, Table 4 presents short-run and long-run findings of the asymmetric ARDL approach along with diagnostic tests. The short-run outcomes show that the positive (negative) component of ER increases (decreases) clean energy consumption. As the estimated coefficient of ER is + 0.173 (-0.081), infer that a 1% increase (decrease) in ER enhance (reduce) clean energy consumption by + 0.173 (-0.081%). These estimates are significant at a 10 percent level of significance. Thus a positive shock in ER is positively linked with clean energy and a negative shock is negatively associated with clean energy consumption. The effects of EM and ET are, however, insignificant. The coefficient of GDP has a positive effect while the coefficient of FDI suggests an insignificant impact.

The long-run outcomes show that the positive (negative) component of ER increases (decreases) clean energy consumption. The estimated positive coefficient shows that a 1% increase in ER enhances clean energy consumption by + 0.309%. However, the negative shock in ER does not have any significant impact on clean energy consumption. Interestingly, EM (ET) is positively connected with clean energy consumption. The numerical values show that a 1 percent increase in EM (ET) will increase demand for clean energy consumption by 0.158 % (0.370 %). The effect of GDP on energy demand is also positive significant and coefficient is 0.580 %. The effect of FDI is, however, not significant.

The short-run CO2 model results show that neither positive nor negative shocks in ER have a significant effect on CO2 emissions in the short run. The effect of ET is, however, negative and insignificant. The coefficient of ET indicates that a 1 % in increase in ET will decrease CO2 emissions by 0.733 %. The coefficient of GDP has a negative effect while the coefficient of FDI suggests an insignificant impact. The long-run outcomes show that the positive component of ER decreases CO2 emissions. The estimated positive coefficient shows that a 1% increase in ER lowers CO2 emissions by - 0.418%. However, the negative shock in ER does not have any significant impact on CO2 emissions. The effect of EM (ET) is positive and significant on CO2 emissions. The numerical values show that a 1 percent increase in EM (ET) will fall CO2 emissions by 0.233% (2.095 %). The GDP is reducing CO2 emissions by 4.532 %. The effect of FDI is, however, not significant.

Table 4: NARDL estimates of clean energy and CO2

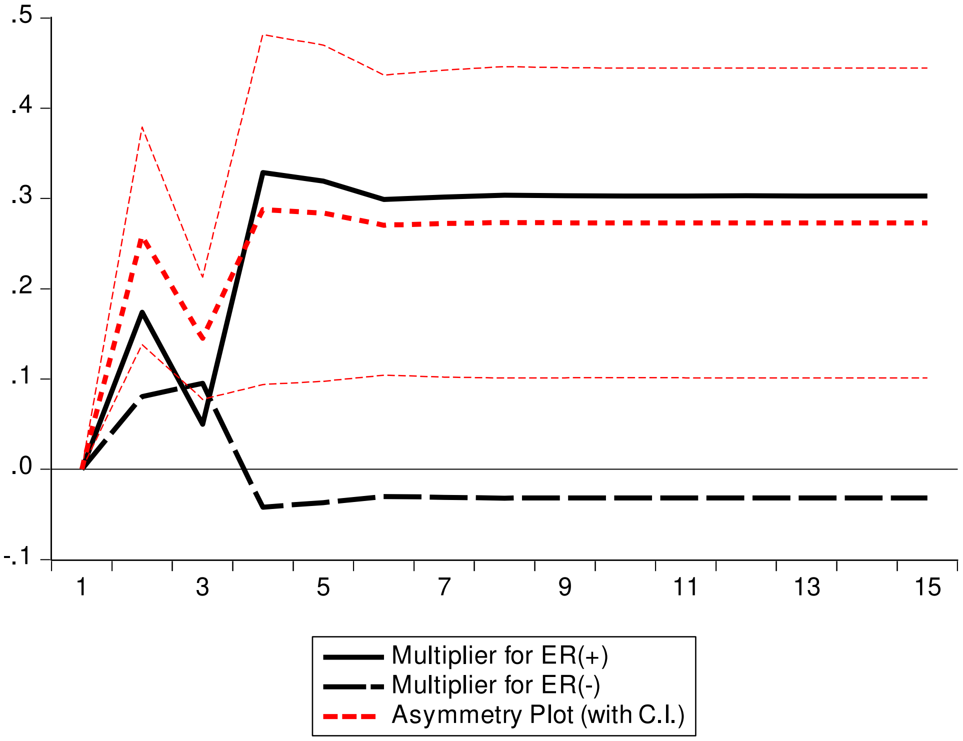
	Clean energy				**CO2**			
Variable	**Coefficient**	**S.E**	**t-Stat**	**Prob.**	**Coefficient**	**S.E**	**t-Stat**	**Prob.**
Short-run								
D(ER_POS)	0.173***	0.063	2.767	0.070	0.025	0.066	0.380	0.713
D(ER_POS(-1))	-0.281**	0.110	2.545	0.084				
D(ER_NEG)	-0.081***	0.014	5.912	0.010	0.005	0.010	0.467	0.652
D(ER_NEG(-1))	-0.131***	0.011	12.10	0.001				
D(EM)	-0.045	0.036	1.248	0.301	0.034	0.024	1.433	0.186
D(EM(-1))	0.091***	0.031	2.937	0.061	0.132***	0.042	3.126	0.012
D(ET)	-0.029	0.083	0.354	0.746	-0.389*	0.203	-1.915	0.069
D(ET(-1))	-0.309***	0.067	4.649	0.019	-0.733***	0.154	4.758	0.001
D(GDP)	1.822***	0.235	7.766	0.004	-0.324	0.489	0.664	0.523
D(GDP(-1))	1.633***	0.349	4.673	0.019	1.761***	0.422	4.178	0.002
D(FDI)	0.260	0.334	0.777	0.494	-0.186	0.308	0.603	0.562
D(FDI(-1))	-0.262	0.164	1.594	0.209				
Long-run								
ER_POS	0.309***	0.071	4.376	0.022	-0.418***	0.067	6.269	0.000
ER_NEG	0.028	0.031	0.888	0.440	0.009	0.019	0.458	0.658
EM	0.158***	0.043	3.676	0.035	-0.233***	0.051	4.594	0.001
ET	0.370***	0.068	5.420	0.012	-2.095***	0.431	4.859	0.001
GDP	0.580***	0.205	2.825	0.067	-4.532***	1.052	4.308	0.002
FDI	0.947	0.587	1.615	0.205	-0.355	0.567	0.626	0.547
C	7.056***	1.165	6.054	0.009	30.97***	4.166	7.436	0.000
Diagnostic								
F-test	4.264***				6.280***			
ECM(-1)	-0.307	0.211	1.454	0.114	-0.523***	0.088	5.939	0.000

LM	1.534	2.010
Hetro	0.709	0.642
RESET	0.226	0.369
CUSUM	S	S
CUSUM-2	S	S
Wald-SR	2.012	1.023
WALD-LR	4.302***	5.325***

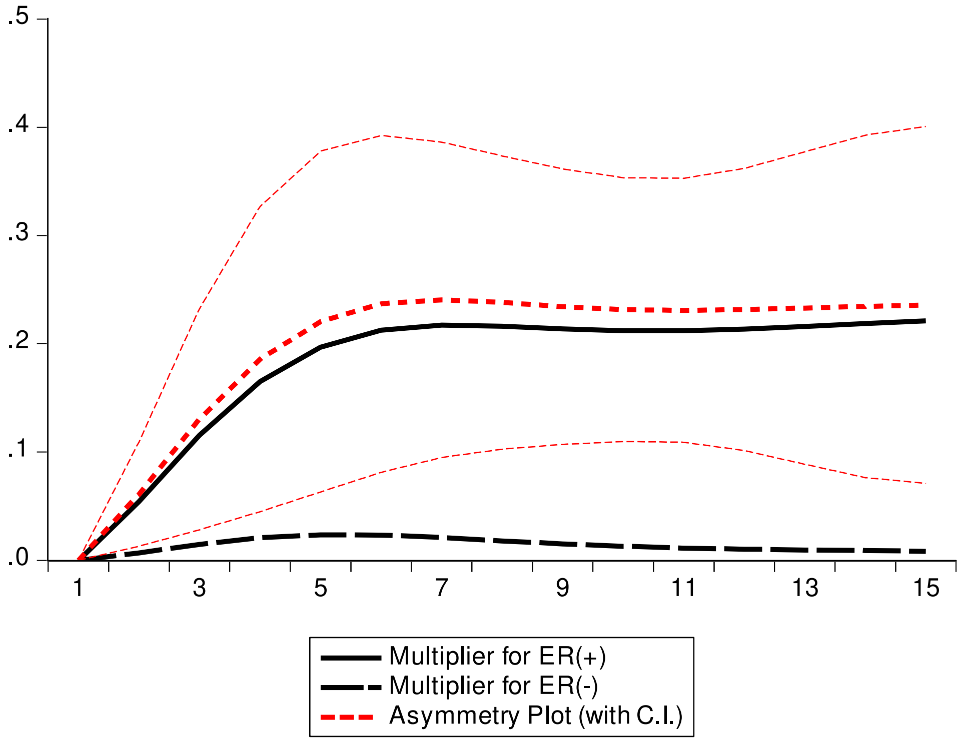
Note: *p<0.1, **p<0.05, and ***p<0.01

Table 4 also presents short-run and long-run asymmetric associations of ER with clean energy are tested using the Wald test. The numerical value of the Wald test for short-run analysis does not reject the hypothesis of the short-run asymmetry while the numerical Wald test for long-run analysis rejects this hypothesis. Thus ER has nonlinear impacts on clean energy only in the long run. Similarly, the Wald test outcome confirms a long-run asymmetry for our second model of CO2 emissions. Thus ER has an asymmetric association with CO2 emissions only in the long run. Moreover, the F-statistics of nonlinear ARDL is statistically significant for both models of clean energy and carbon emission. Thus we can infer that cointegration exists among selected variables in both models. The "error correction term (ECT)" for both models is negative significant, confirming the presence of cointegration among the selected variables. Particularly, the coefficients of ECT show that clean energy (CO2 emission) readjust their long-run equilibrium, with a rate of 31% (52%) each year. Besides, the nonlinear ARDL also qualifies the main diagnostic tests comprising "Ramsey RESET, Heteroskedasticity, R2 and LM test." Figures 1 and 2 provide a multiplier graph for clean energy consumption and CO2 emissions, respectively. Figure 1 depicts that initially both shocks in ER cause deviation from the equilibrium then both converge towards the equilibrium. Overall the positive shock in ER remains dominant during the adjustment process. Figure 2 also indicates that the positive shock in the CO2 model remains dominant during the adjustment process.

Multiplier graph for clean energy consumption



Multiplier graph for CO2 emissions



Conclusions and policy

There is growing empirical evidence that the effect of environmental regulation on clean energy consumption and CO2 emissions may not be linear. To this end, a plethora of empirical literature has examined the possibility of a non-linear nexus between environmental regulations on CO2 in China and well documented by Wang et al. (2019). The previous linear model faced problems in empirical estimates, signifying the essential of nonlinear estimation techniques in the energy and environmental production model (Ullah et al. 2020).

By relaxing the linearity hypothesis, this study examined the nonlinear influence of environmental regulation on clean energy consumption and carbon emissions in China. The linear ARDL results show that environmental regulation has a promotional effect on clean energy consumption; however, environmental regulations in China lead to a reduction in CO2 emissions in the short-run and long. The linear findings also show that environmental monitoring and environmental technology have a better long-term effect on clean energy consumption and environmental quality, but environmental-related technological improvements inspired by consumption of clean energy, in return improve the quality of the environment in long-term incentives. Thus linear findings show that environmental regulation, environmental monitoring, and environmental technology are reasonable sources of the green economy. The nonlinear estimates show that the positive shock of environmental regulation has positively influenced clean energy consumption in the short and long-term, while the negative shock of environmental regulation has to decrease clean energy in the only short run. Accordingly, a positive shock has reduced CO2 emissions, and ultimately, induce environmental quality in the only long run. Our findings show that the environmental regulation shocks have different magnitude and similar signs in clean energy consumption, while it has different magnitude and opposite signs in CO2 emissions. The results show that nonlinear estimates of focused variables deviate from the linear models.

Based on these findings, market-based environmental regulations can encourage economic as well energy efficiency. There is also a necessity to set a possible level of environmental regulation and authority should reinforce the environmental regulation in the economy. The government should increase smart technology to reduce fossil fuel energy intensity and follow the route of green growth. Developing clean energy and upgrading the digitization structure of the economy is a forward-thinking policy. China should impose a carbon tax on pollutant industries. China should increase regulatory efficiency by attaining the goals of carbon emissions reductions. Carbon pricing might be an effective policy tool to improve environmental quality, authorities should also reconsider the institutions in environment quality. China can correct the environment by using regulations for green growth purposes.

Although this study assessed the asymmetric impact of environmental regulation on clean energy and carbon emissions using a nonlinear model, the study is still introductory. The empirical study did not include a provincial analysis and so sub-national level analysis is provides targeted policies by using the nonlinear ARDL. Our research work does not explore asymmetric determinants of green growth. There is much space for the further expansion of the model. The proposed empirical approach can also be applied to examine the clean energy and environmental efficiency of sector-wise in China at micro-level data. Furthermore, the influence of carbon taxes on various sectors of the economy, such as industry, agriculture, transport, automobile, etc., can also be considered in the forthcoming studies.

Ethical Approval: Not applicable

Consent to Participate: I am free to contact any of the people involved in the research to seek further clarification and information

Consent to Publish: Not applicable

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Availability of data and materials: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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