

Revisit coal consumption, CO₂ emissions and economic growth nexus in China and India using a newly developed bootstrap ARDL bound test

Feng-Li Lin,¹ Roula Inglesi-Lotz² and Tsangyao Chang³

Abstract

This study revisits coal consumption, CO₂ emissions and economic growth nexus for both China and India using a newly developed Bootstrap ARDL model over the period of 1969–2015. Empirical results indicate no long-run relationship among these three variables for both China and India, and Granger causality test based on Bootstrap ARDL model indicates a feedback between coal consumption and economic growth, between economic growth and CO₂ emissions and between coal consumption and CO₂ emissions in China. However, we find a one-way Granger causality running from coal consumption to economic growth and the feedback hypothesis is confirmed between economic growth and CO₂ emissions and between coal consumption and CO₂ emissions in India. The coefficients signal that coal consumption is an important factor towards the promotion economic growth in both China and India. For China, higher economic growth reduces CO₂ emissions, while for India, it further increases CO₂ emissions. Our empirical results have important policy implications for the government conducting effective energy polices to promote economic growth in both China and India.

Keywords

Coal consumption, CO₂ emissions, economic growth, bootstrap ARDL bound test, China and India

¹Department of Accounting, ChaoYang University, Taichung, Taiwan

²Department of Economics, University of Pretoria, Pretoria, South Africa

³Department of Finance, Feng Chia University, Taichung, Taiwan and CTBC Financial College of Management, Tainan, Taiwan

Corresponding author:

Roula Inglesi-Lotz, University of Pretoria, Tukkiewerf Building, Main Campus, Pretoria 0002, South Africa.

Email: roula.inglesi-lotz@up.ac.za



Introduction

Both China and India are not only the two largest coal consumption countries but also two of the largest CO₂ emission countries in the world. For the past decade, China and India experience a steady increase in their energy use, especially coal and oil, such that in aggregate, it is expected that they will consume 45% of the world's coal in 2030 (Jayanthakumaran et al., 2012). China has per capita CO₂ emissions of 26.31 tonnes and India has per capita CO₂ emissions or 22.39 tonnes during the period of 1969–2015 (BP, 2014).

Both China and India are confronted with double challenges – addressing climate change in the international society and environmental protection with domestic economic transition in combination with increasingly high needs for energy – that based on their current supply mixes come from coal consumption that is considered amongst the main reasons of pollution.

From Figures 1 and 2, it could be seen that coal consumption and CO₂ emissions are increasing steadily in both China and India. This means air pollution is an important issue for both countries. The IEA *Medium-Term Coal Market Report* (IEA, 2011) noted that this boost in coal demand corresponds to rising coal usage, which amounted to approximately 720,000 tonnes every day since 2011.¹ As of March 2012, approximately 40% of the world's electricity needs were provided by coal. Growth in coal demand varies from country to country: while coal consumption has stagnated among OECD countries since the beginning of the 21 first century, the surge in global coal consumption is driven primarily by developing economies, such as China and India. Economic growth is likely to be robust in both China and India over the next several years. If these trends continue, by 2020, China will become the largest and India the third-largest economy in the world. This rapid economic growth is likely to be associated with increased energy use and increased air pollution. Because coal is

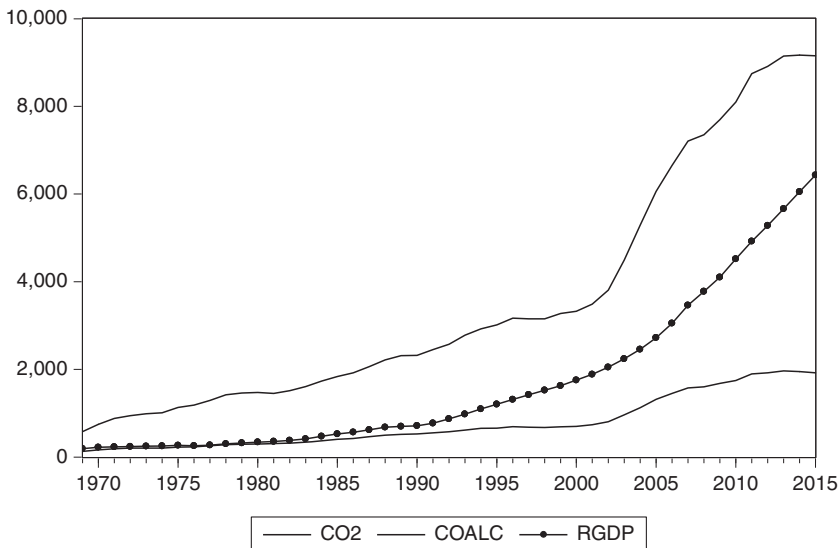


Figure 1. Plots of real GDP, coal consumption and CO₂ emissions in China.

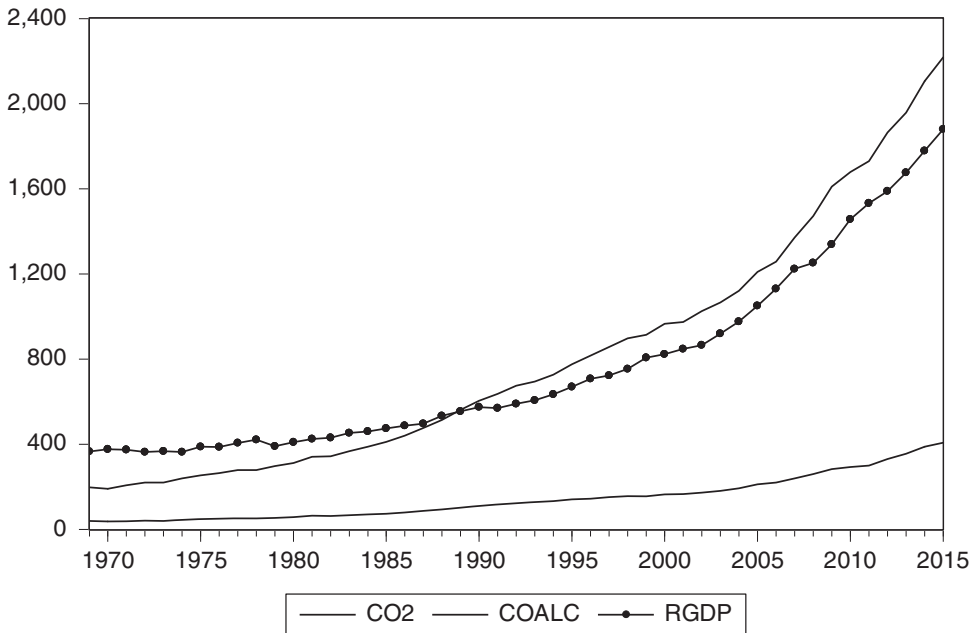


Figure 2. Plots of Real GDP, coal consumption and CO₂ emissions in India.

the key fuel in both countries' energy mix and since economic growth and energy use are highly correlated, coal demand prospects for both countries are expected to be bullish in 2017. Thus, knowledge of the causal relationship and the direction between energy consumption, CO₂ emissions and economic growth are of particular importance to policy makers from China and India to make an appropriate energy strategy.

To evaluate the trivariate relationship between coal consumption, CO₂ emissions and economic growth in these two countries (China and India), this paper is going to use a specific ARDL econometric methodology. Since Pesaran et al. (2001) developed their ARDL bound test, this test has gone through several types of transformation. For example, single ARDL test of Li and Lee (2011), Nonlinear ARDL test of Shin et al. (2014) and System ARDL test of Li (2017). Recently, McNown et al., (2016) have further modified this test through bootstrap techniques and this newly developed bootstrap ARDL bound test has several advantages over conventional ARDL bound test of Pesaran et al. (2001).

The first advantage of Bootstrap ARDL bound test is that there is evidence that the endogeneity problem has only minor effects on the size and power properties of the ARDL bounds testing framework using the asymptotic critical values from the Monte Carlo simulations. In addition, if the resampling procedure is applied appropriately, the bootstrap test performs better than the asymptotic test in the ARDL bounds test based on size and power properties. Second, the bootstrap procedure has the additional advantage of eliminating the possibility of inconclusive inferences. Finally, but of significance, they present an extension of the ARDL testing framework for the alternative degenerate case, with critical values generated by the bootstrap procedure. Therefore, their proposed bootstrap ARDL test provides a better insight on the cointegration status of the series in the model.

This study revisits the coal consumption, CO₂ emissions and economic growth nexus for both China and India using this newly developed Bootstrap ARDL model over the period of 1969–2015. This study is organized as follows. The next section describes the data used in our study. The subsequent section first briefly describes the traditional ARDL models of Pesaran and then describes the proposed new Bootstrap ARDL model of McNown et al. (2016). Then the empirical results and some policy implications of these empirical findings are presented. The last section offers the conclusions of this study.

Brief literature review

Evidently, the international energy literature has shown high interest in the examination of the energy-environment-economy nexus for different countries over different periods. The trivariate relationship was traditionally examined in two parts: the energy-growth and the growth-environmental degradation (air pollution in the form of emissions primarily) (Bekhet et al., 2017).

For the first strand of the literature, Kraft and Kraft (1978) have put the foundations towards the dynamics of the relationship between energy consumption and economic growth and energy consumption. Ozturk and Acaravci (2010) have presented an extended energy-growth survey showing that there is no consensus among the studies. Menegaki (2014) conducted a meta-data analysis of more than 150 papers with global data since 1949; this study showed that the existence and direction of the causality between GDP and energy consumption are highly dependent to the method and data used. Inglesi-Lotz and Pouris (2016) in a review paper for the nexus in South Africa confirmed the same conclusion. They also suggested that the inclusion of other factors in the analysis is also crucial for the results. Kalimeris et al. (2014) also discussed the complexity of the relationship and the impact of scarcity of resources for example might have on it. The literature is attracted by the lack of consensus, and hence a number of studies attempted to provide more robust results (Almulali et al., 2013; Apergis and Payne, 2011; Chang et al., 2017, 2016; Dergiades et al., 2013; Eggoh et al., 2011; Ozturk and Acaravci, 2010; Tang, 2008; Wang et al., 2011).

The inclusion of the environmental status quo of a country proxied by its emissions within the nexus examination is related to the Environmental Kuznets Curve (EKC) hypothesis. Firstly proposed by Grossman and Krueger (1991) and extensively discussed in Stern (2004) and Dinda (2004), the hypothesis postulates that the relationship between economic development (growth) has an inverted-U relationship with the environmental pollution levels of the country. Acaravci and Ozturk (2010) found that there is a bidirectional relationship from energy consumption to CO₂ emissions for a group of 19 European countries. A strong relationship between CO₂ emissions and economic growth was found in Saboori et al. (2014) for the OECD countries. Menyah and Wolde-Rufael (2010a, 2010b) examined the relationship between CO₂ emissions, renewable and nuclear energy consumption, and real GDP for US finding that there is a unidirectional causality from nuclear to emissions but no causality from renewable consumption to emissions. A number of other studies have also tried to evaluate that relationship (Alam et al., 2012; Iwata et al., 2010; Pao and Tsai, 2011; Shahbaz and Lean, 2012; Shahbaz et al., 2012).

Methodology

ARDL bound test (Pesaran et al. 2001)

Following Pesaran et al. (2001), we can write our ARDL bound model as the follows

$$\Delta Y_t = c + \alpha Y_{t-1} + \beta X_{t-1} + \sum_{i=1}^{p-1} \theta \Delta Y_{t-i} + \sum_{i=1}^{p-1} \delta X_{t-i} + \sum_{j=1}^q \eta D_{t,j} + \varepsilon_t \quad (1)$$

And equation (1) requires no feedback from Y to X . This means that we cannot allow two or more variables to be (weakly) endogenous and this violates the assumptions underlying the distributions of the test statistics presented by Pesaran et al. (2001). It assumes weak exogeneity of the regressors. These regressors are not impacted by the dependent variable in the long run, but this does not preclude the existence of cointegration among the regressions, nor does it assume the absence of (short run) Granger causality from the dependent variable to the regression. Many researchers ignore this assumption in the empirical implications of the ARDL bounds test.

Following Pesaran et al. (2001), the cointegration test requires F-test or t-test for the following hypothesis: $H_0 : \alpha = \beta = 0$ or $H_0 : \alpha = 0$

Bootstrap ARDL bound test (McNown et al. 2016)

McNown et al. (2016) suggest adding an additional t-test $H_0 : \beta = 0$ to complement the existing F and t-tests for cointegration proposed by Pesaran et al. (2001). The use of all three tests is necessary to distinguish between cases of cointegration, noncointegration and degenerate cases defined by Pesaran et al. (2001). Based on McNown et al. (2016), we can define the two degenerate cases as follows:

- **Degenerate case #1** occurs when the F-test and the t-test on the lagged independent variable are significant, but the t-test on the lagged dependent variable is insignificant.
- **Degenerate case #2** occurs when the F-test and the t-test on the lagged dependent are significant, but the lagged independent variables are not significant.

Pesaran et al. (2001) present critical values for case #2, but not for case #1. To rule out degenerate case #1, the integration order for the dependent variable must be I(1). However, unit root tests are notorious for having low power (Perron, 1989). The Bootstrap ARDL test tackles this problem through additional test on the coefficients of the lagged independent variables. The advantage of Bootstrap ARDL bound test is that there is evidence that the endogeneity problem has only minor effects on the size and power properties of the ARDL bounds testing framework using the asymptotic critical values from the Monte Carlo simulations. In addition, if the resampling procedure is applied appropriately, the Bootstrap test performs better than the asymptotic test in the ARDL bounds test based on size and power properties. Furthermore, the Bootstrap procedure has the additional advantage of eliminating the possibility of inconclusive inferences. Finally, McNown et al. (2016) also present an extension of the ARDL testing framework for the alternative degenerate case, with critical values generated by the Bootstrap procedure. Therefore, the proposed Bootstrap ARDL test provides a better insight on the cointegration status of the series in the model.

Granger causality test based on bootstrap ARDL model

The direction of the short-run causal relationship will be determined by standard Granger-causality tests. If no cointegration is found between y and x when y is the dependent variable, then the Granger causality test for $x \geq y$ should include the lagged differences on x only, that is, we test whether $\delta = 0$. However, if cointegration exists among the variables, then this means the dependent and the independent variables form a stationary linear combination. As a result, the lagged levels can be treated as $I(0)$. In this case, the Granger-causality test for $x \geq y$ should include the lagged differences on x and the lagged level of x , i.e. test whether $\beta > 0$ and $\delta = 0$. We can also extend the equation (1) to three-variable case (see the following model)

$$\begin{aligned} \Delta Y_t = & c + \alpha Y_{t-1} + \beta X_{t-1} + \gamma Z_{t-1} + \sum_{i=1}^{p-1} \theta \Delta Y_{t-i} + \sum_{i=1}^{p-1} \delta \Delta X_{t-i} \\ & + \sum_{i=1}^{p-1} \omega Z_{t-i} + \sum_{j=1}^q \eta D_{t,j} + \varepsilon_t \end{aligned} \quad (2)$$

In this case, the Granger-causality test for $x \geq y$ should include the lagged differences on x and the lagged level of x , i.e. test whether $\beta > 0$ and $\delta = 0$. For $z \geq y$ should include the lagged differences on z and the lagged level of z , i.e. test whether $\gamma > 0$ and $\omega = 0$ (if they are cointegrated).

The Bootstrap ARDL approach to cointegration testing has several interesting characteristics. First, it performs better to small samples compared to alternative multivariate cointegration procedures (Romilly et al., 2001). Second, it does not require the restrictive assumption that all series are integrated of the same order allowing for the inclusion of both $I(0)$ and $I(1)$ (but not $I(2)$) time series in a long-run relationship. The latter provides flexibility and also avoids potential “pre-test bias,” that means, the specification of a long-run model on the basis of $I(1)$ variables only (Pesaran et al., 2001).

Data

We apply annual data covering the period from 1969 to 2015 for both China and India. The variables used in this study include the real gross domestic product (GDP), Coal consumption (Coale) and CO₂ emissions (CO₂). Coal consumption and CO₂ emissions are expressed in terms of millions of tonnes for both China and India and are sourced from the BP Statistic Review of World Energy (June, 2016). Real GDP for both China and India is from the World Development Indicators (WDI; The World Bank, 2016).

Tables 1 to 3 report the summary statistics for the data series. China has higher growth rate, coal consumption and CO₂ emissions than those of India. Figures 1 and 2 show time series plots of these three variables for China and India, respectively. We find that all three variables are trending upwards for both China and India. Jarque-Bera statistics indicate that all three variables are non-normally distributed for both China and India during this time period.

Table 1. Summary statistics of GDP growth.

Country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
China	0.076	0.15032	-0.03211	0.03444	-0.7095	4.217	6.702**
India	0.0356	0.08375	-0.07369	0.03037	-1.129	5.145	18.59***

Note: The sample period is from 1969 to 2015.

GDP: gross domestic product. **(***) denote 5% (1%) level of significance.

Table 2. Summary statistics of coal consumption (million).

Country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
China	766.61	1964.37	130.41	587.22	0.953	2.495	7.62**
India	144.11	407.217	37.558	101.360	1.000	3.093	7.85**

Note: The sample period is from 1969 to 2015. ** denote 5% level of significance.

Table 3. Summary statistics of CO₂ emissions (million).

Country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
China	3557.69	9165.52	582.76	2723.68	0.9774	2.546	7.88**
India	809.107	2218.434	190.35	571.66	0.8912	2.767	6.33**

Note: The sample period is from 1969 to 2015. ** denote 5% level of significance.

Empirical results and policy implications

Results from the unit root test

Because the Bootstrap ARDL bound test approach does not require the restrictive assumption that all series are integrated of the same order, thus allowing for the inclusion of both $I(0)$ and $I(1)$ time series in a long-run relationship, the presence of $I(2)$ variables turns the computed F_{PSS} statistic invalid (Pesaran et al., 2001). Therefore, we need to first go for several conventional unit root tests such as the ADF, PP (Phillips and Perron, 1988), and KPSS (Kwiatkowski et al., 1992). Table 4 reports the results from several conventional unit root tests, which all suggest that these three variables employed are all non-stationary in levels, while they turn stationary in first differences for both China and India.

Results from bootstrap ARDL bound test – Cointegration test

Because all variables are integrated of one or zero (or $I(1)$ and $I(0)$), we proceed to test for cointegration by employing the Bootstrap ARDL bound test approach for both China and India. The selection of the optimal Bootstrap ARDL specifications is selected based on the Schwarz information Criterion which is asymptotically consistent for the lag length and is favored by Pesaran and Shin (1999). The selection of the optimal ARDL specifications is

Table 4. Univariate unit root tests.

Country	Item	Level			First differences		
		ADF	PP	KPSS	ADF	PP	KPSS
China	CO ₂	-0.216575(1)	-1.47529(3)	0.883954(5)***	-4.626327(0)***	-4.626327(0)***	0.156883(3)
	Coalc	0.346391(1)	-1.334217(3)	0.879991(5)***	-3.357932(2)**	-4.662639(2)***	0.134903(2)
	GDP	1.252936(2)	1.569321(2)	0.885537(5)***	-3.323747(1)**	-4.871916(3)***	0.333772(3)
India	CO ₂	0.908126(0)	0.958845(3)	0.891754(5)***	-4.337308(1)***	-8.715239(2)***	0.165957(3)
	Coalc	1.476334(0)	1.500105(1)	0.889367(5)***	7.150453(0)**	-7.206909(1)***	0.265791(2)
	GDP	3.952915(0)	4.746705(3)	0.863570(5)***	-5.450174(0)***	5.607776(4)***	0.842196(4)***

Notes: ***, ** and * indicate the null hypothesis is rejected at the 1%, 5% and 10% levels, respectively. The number in brackets indicates the lag order selected based on Schwarz information criterion. The number in the parenthesis indicates the truncation for the Bartlett Kernel, as suggested by the Newey-West test (1987).

Table 5. Cointegration results using bootstrap ARDL bound test – China.

China	DV IV	Dummy variables	F	F* ₋	Tdep	T* _{dep}	Findep	F* _{indep}	Result
GDP[2]	GDP Coalc, CO ₂	d95 d06	0.460	183.26	-0.282	3.173	0.149	9.66	No cointegration
Coalc[2]	Coalc GDP, CO ₂	D88 d04	1.011	14.25	-1.321	-1.687	1.517	189.46	No cointegration
CO ₂ [2]	CO ₂ GDP, Coalc	D88 d04	1.060	7.148	-0.104	0.621	1.538	4.117	No cointegration

(1969–2015)

Notes: [.] is optimal lag order based on Akaike Information Criterion (AIC). F is the F-statistic for the coefficients of $yt-1$, $x t-1$ and $zt-1$; Tdep denotes the t-statistics for the dependent variable, Tindep denotes the t-statistics for the independent variable. F*, T_{dep} and T_{indep} are the critical values at 5% significance level, generated from the bootstrap program. Dummy variables are to capture any economics shocks. D41 means 1 for year 1941, other years are 0.

based on a general-to-specific approach, starting with $max p = max q = 4$ and dropping all the insignificant lags using a 5% decision rule. The F_{PSS} statistics of the Bootstrap ARDL approach being reported in Tables 5 and 6 indicate strong evidence in favor of the non-existence of a long-run cointegrating relationship among economic growth (GDP), coal consumption and CO₂ emissions in both China and India. Therefore, we proceed to test the Granger causality test based on our Bootstrap ARDL model in difference.

Granger causality test results based on bootstrap ARDL model and policy implications

Table 7 reports Granger causality test results based on Bootstrap ARDL model for China. From Table 7, a feedback relationship exists between economic growth (GDP) and CO₂ emission, between economic growth (GDP) and coal consumption and between CO₂ emissions and coal consumption. Looking at the sign of all coefficients of all independent variables, both coal consumption and CO₂ emissions are important determinants of economic

Table 6. Cointegration results using bootstrap ARDL bound test – India.

India	DV IV	Dummy variables	F	F*_	Tdep	T*dep	Findep	F*indep	Result
GDP[2]	GDP Coalc, D81 d88 d98 d07 CO ₂		4.407	4.869	-1.013	-3.280	2.508	6.451	No cointegration
Coalc [2]	Coalc GDP, D81 d90 d05 CO ₂		1.123	130.14	-1.245	1.695	1.484	74.37	No cointegration
CO ₂ [2]	CO ₂ GDP, D81 d90 d97 d05 Coalc		0.233	3.254	0.616	-2.158	0.337	4.11	No cointegration

(1969–2015)

Notes: [.] is optimal lag order based on Akaike Information Criterion (AIC). F is the F-statistic for the coefficients of $yt-1$, $x t-1$ and $zt-1$; Tdep denotes the t-statistics for the dependent variable, Tindep denotes the t-statistics for the independent variable. F*, T_dep and T_indep are the critical values at 5% significance level, generated from the bootstrap program. Dummy variables are to capture any economics shocks. D41 means 1 for year 1941, other years are 0.

Table 7. ARDL granger-causality analysis – China.

China	Δ GDP equation: Δ Coalc, Δ CO ₂ , F-statistics (p-value) (Sign)	Δ Coalc equation: Δ GDP, Δ CO ₂ , F-statistics (p-value) (Sign)	Δ CO ₂ equation: Δ GDP, Δ Coalc, F-statistics (p-value) (Sign)
GDP	n.a.	4.802*** (0.015)(-)	20.590*** (0.000) (-)
Coalc	36.095*** (0.000)(+)	n.a.	83.007*** (0.000) (+)
CO ₂	33.359*** (0.000)(-)	10.245*** (0.0004)(-)	n.a.

Note: Value in [.] is lag order, and (.) are p-value and sign for the coefficients. Bold values in the first row refer to the specific construction of the long-run equation tested for cointegration and the causality test involved its lagged level and differenced variables (for example, Δ GDP equation means that the differenced GDP is the dependent). Those values not in bold refer to the case of no-cointegration and its causality test involved only lagged differenced variables. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

growth (GDP) in China. Here, coal consumption promotes economic growth; however, we find economic growth further decreases coal consumption in China because we find the signs are positively statistically significant in one direction and negative in the other direction.

On the other hand, CO₂ emissions harm economic growth and economic growth further reduces CO₂ emissions in China because we find the signs are neither positive nor significant in either direction. Coal consumption increases along with the increase of CO₂ emissions; however, CO₂ emissions increase along with the decrease of coal consumption in China.

These empirical findings indicate that when economic growth increases (and people live in better conditions and healthier environment), people will need clear air and government in China sets up clean-air policy to reduce CO₂ emissions and at the meantime when CO₂ emissions increase then coal consumption decreases. That leads the Chinese policy makers to look for appropriate policies for energy substitution.

Our study supports energy-led growth in China. However, this policy might create air pollution in China. It seems that the government in China did well in combating air pollution because we find that when coal consumption increases, the government also tries to reduce CO₂ emissions and when CO₂ emissions increase, to control for this continue climbing CO₂ emissions, the government reduces coal consumption. However, this might

Table 8. ARDL granger-causality analysis – India.

India	ΔGDP equation: $\Delta Coal_c, \Delta CO_2,$ F-statistics (p-value) (Sign)	$\Delta Coal_c$ equation: $\Delta GDP, \Delta CO_2,$ F-statistics (p-value) (Sign)	ΔCO_2 equation: $\Delta GDP, \Delta Coal_c,$ F-statistics (p-value) (Sign)
GDP	n.a.	0.364 (0.698)(-)	2.203 (0.128) (+)
Coal _c	11.922*** (0.000)(+)	n.a.	21.792*** (0.000) (+)
CO ₂	5.243** (0.0111)(-)	11.585*** (0.0002)(-)	n.a.

Notes: Value in [.] is lag order, and (.) are p-value and sign for the coefficients. Bold values refer to the case of cointegration and the causality test involved its lagged level and differenced variables. Those values not in bold refer to the case of no-cointegration and its causality test involved only lagged differenced variables. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

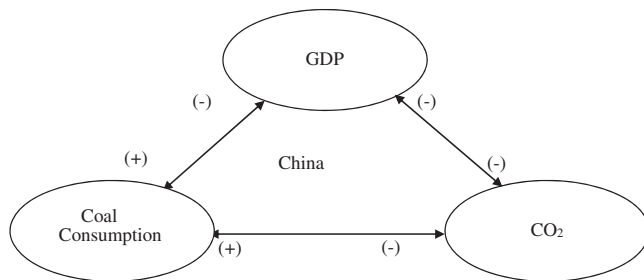


Figure 3. Causal link among GDP, CO₂ emissions and coal consumption in China.

further harm economic growth in China. The major policy implication of our study is that government in China should set up an effective-energy strategy for not only promoting economic growth but also controlling the CO₂ emissions.

Table 8 reports Granger causality test results based on Bootstrap ARDL model for India. From Table 8, we find a one-way Granger causality running from coal consumption to GDP (economic growth). This result further supports energy-led growth hypothesis in India. On the other hand, empirical findings also find a feedback exist between economic growth (GDP) and CO₂ emissions and between coal consumption and CO₂ emissions. Looking at the sign of all coefficients of all independent variables and we further confirm that coal consumption is an important contributor to economic growth in India. Interesting is that we also find economic growth reduces coal consumption in India. On the one hand, economic growth further increases CO₂ emissions in India. Coal consumption and CO₂ emissions reinforce each other in India. Coal consumption increases CO₂ emissions; however, when increase in CO₂ emissions further reduces coal consumption in India. These empirical results mean coal consumption promoted economic growth and to reduce CO₂ emissions, India further reduces coal consumption to reduce CO₂ emissions. Our empirical results have important policy implications for the government of India conducting effective energy polices to promote economic growth and control CO₂ emissions in India.

Figures 3 and 4 demonstrate the causal relationship among these three variables (i.e. economic growth (GDP), CO₂ emissions and coal consumption) for China and India,

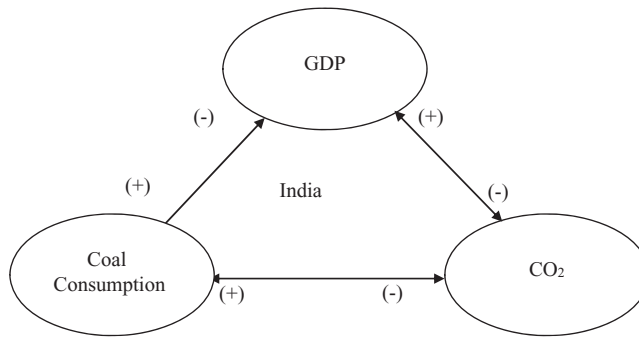


Figure 4. Causal link among GDP, CO₂ emissions and coal consumption in India.

respectively, and these two figures further confirm our empirical findings, which support the energy-led growth hypothesis for India and economic growth and coal consumption reinforce each other in China supporting feedback hypothesis.

This result is consistent with those of Wang et al. (2011) and Bloch et al. (2012) revealing that there is bi-directional causality between coal consumption and pollutant emission both in the short and long run for both China and India and unidirectional causality from coal consumption to economic growth in India. Hence, it is very difficult for both China and India to pursue a greenhouse gas abatement policy through reducing coal consumption. Switching to greener energy sources might be a possible alternative in the long run. The results indicate that CO₂ emissions in both China and India will not decrease in a long period of time and reducing CO₂ emissions may handicap both China's and India's economic growth to some degree.

However, our results are not consistent with those of Li et al. (2011), Li and Lee (2011) and Li and Leung (2012), and Rafiq et al. (2014) found that a unidirectional causality running from economic growth to coal consumption existed in China, while a unidirectional causality from coal consumption to GDP did exist in India. Results are also not consistent with that of Chang (2010) supporting a unidirectional causality from output to both energy consumption and CO₂ emissions and Yalta and Cakar (2012) supporting neutrality hypothesis in 53 out of 60 models estimated in China. Possible differences in the results might arise from the difference in the examined time periods and the inclusion of control variables and methodologies used (Inglesi-Lotz and Pouris, 2016).

Conclusions

We revisit the relationship between coal consumption, CO₂ emissions and economic growth for both China and India using a newly developed Bootstrap ARDL model over the period of 1969–2015. Results indicate no long-run relationship among these three variables for both China and India and results from Granger causality test based on Bootstrap ARDL model indicate a feedback between coal consumption and economic growth, between economic growth and CO₂ emissions and between coal consumption and CO₂ emissions in China. However, we only find a one-way Granger causality coal consumption to economic growth and a feedback exists between economic growth and CO₂ emissions and between coal consumption and CO₂ emissions in India. By looking at the sign of coefficients of the

independent variable, we find that coal consumption is a very important energy source for promoting economic growth in both China and India. Interesting is that we find economic growth reduce coal consumption in both China and India.

Our empirical results support energy-led growth hypothesis for India and feedback hypothesis for China. On the hand, we also find economic growth reduces CO₂ emissions in China; however, economic growth further increases CO₂ emissions in India. Regarding coal consumption and CO₂ emissions, we find these two variables reinforce each other in both China and India. Coal consumption increases CO₂ emissions but increase in CO₂ emissions further reduces coal consumption in both China and India.

Thus, knowing the causal relationship and the direction between energy consumption, economic growth and CO₂ emissions are of particular importance to policy makers to make an appropriate energy strategy. Our empirical results have important policy implications for the government conducting effective energy policies to promote economic growth and controlling CO₂ emissions in both China and India. Therefore, developing cleaner and more efficient technologies is essential to reduce their CO₂ emissions to reach sustainable development.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Note

1. Since the start of the 21st century, coal production has been the fastest-growing global energy source. It is the second source of primary energy in the world after oil, and the first source of electricity generation.

References

- Acaravci A and Ozturk I (2010) On the relationship between energy consumption, CO₂ emissions and economic growth in Europe. *Energy* 35(12): 5412–5420.
- Alam MJ, Begum IA, Buysse J, et al. (2012) Energy consumption, carbon emissions and economic growth nexus in Bangladesh: Cointegration and dynamic causality analysis. *Energy Policy* 45: 217–225.
- Al-mulali U and Lee JYM (2013) Estimating the impact of the financial development on energy consumption: Evidence from the GCC (Gulf Cooperation Council) countries. *Energy* 60: 215–221.
- Apergis N and Payne JE (2011) The renewable energy consumption–growth nexus in Central America. *Applied Energy* 88: 343–347.
- Bekhet HA, et al. (2017) CO₂ emissions, energy consumption, economic growth, and financial development in GCC countries: Dynamic simultaneous equation models. *Renewable and Sustainable Energy Reviews* 70: 117–132.
- Bloch H, Rafiq S and Salim R (2012) Coal consumption, CO₂ emission and economic growth in China: Empirical evidence and policy responses. *Energy Economics* 34: 518–528.
- BP (2014) *BP Statistical Review of World Energy*. Paris: Author.

- Chang CC (2010) A multivariate causality test of carbon emissions, energy consumption and economic growth in China. *Applied Energy* 87: 3533–3537.
- Chang T, Deale FW, Gupta R, et al. (2017) The causal relationship between coal consumption and economic growth in the BRICS countries: Evidence from panel-Granger causality test. *Energy sources Part B: Economics, Planning and Policy* 12(2): 138–146.
- Chang T, Gupta R, Inglesi-Lotz R, et al. (2016) The causal relationship between natural gas consumption and economic growth: Evidence from the G7 countries. *Applied Economics Letters* 23(1): 38–46.
- Dergiades T, Martinopoulos G and Tsoulfidis L (2013) Energy consumption and economic growth: Parametric and non-parametric causality testing for the case of Greece. *Energy Economics* 36: 686–697.
- Dinda S (2004) Environmental Kuznets Curve Hypothesis: A survey. *Ecological Economics* 49(4): 431–455.
- Eggoh JC, Bangake C and Rault C (2011) Energy consumption and economic growth revisited in African countries. *Energy Policy* 39: 7408–7421.
- Grossman G and Krueger A (1991) Environmental impacts of a North American free trade agreement. National Bureau of Economics Research Working Paper, No. 3194, NBER Cambridge.
- IEA (2011) *Medium-Term Coal Market Report*. Paris: International Energy Agency.
- Inglesi-Lotz R and Pouris A (2016) On the causality and determinants of energy and electricity consumption in South Africa: A review. *Energy Sources, Part B: Economics, Planning, and Policy* 11(7): 626–636.
- Iwata H, Okada K and Samreth S (2010) Empirical study on the environmental Kuznets curve for CO₂ in France: The role of nuclear energy. *Energy Policy* 38: 4057–4063.
- Jayanthakumaran K, Verma R and Liu Y (2012) CO₂ emissions, energy consumption, trade and income: A comparative analysis of China and India. *Energy Policy* 42: 450–460.
- Kalimeris P, Richardson C and Bithas K (2014) A meta-analysis investigation of the direction of the energy- GDP causal relationship: implications for the growth-degrowth dialogue. *Journal of Cleaner Production* 67: 1–13.
- Kraft J and Kraft A (1978) On the relationship between energy and GNP. *The Journal of Energy and Development* 3(2): 401–403.
- Kwiatkowski D, Phillips P, Schmidt P, et al. (1992) Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics* 54: 159–178.
- Li F, Dong S, Li X, et al. (2011) Energy consumption-economic growth relationship and carbon dioxide emissions in China. *Energy Policy* 39: 568–574.
- Li J (2017) System-equation ADL test for threshold cointegration with an application to the term structure of interest rates. *Oxford Bulletin of Economics and Statistics* 79(1): 1–24.
- Li J and Lee Z (2011) A Causality analysis of coal consumption and economic growth for China and India. *Natural Resources* 2: 54–60.
- Li R and Leung GCK (2012) Coal consumption and economic growth in China. *Energy Policy* 40: 438–444.
- McNown R, Sam CY and Goh SK (2016) *Bootstrapping the autoregressive distributed lag test for cointegration*. Department of Economics, University of Colorado at Boulder, Working Paper 16-08.
- Menegaki AN (2014) On energy consumption and GDP studies; A meta-analysis of the last two decades. *Renewable and sustainable energy reviews* 29: 31–36.
- Menyah K and Wolde-Rufael Y (2010a) Energy consumption, pollutant emissions and economic growth in South Africa. *Energy Economics* 32: 1374–1382.
- Menyah K and Wolde-Rufael Y (2010b) CO₂ emissions, nuclear energy, renewable energy and economic growth in the US. *Energy Policy* 38: 2911–2915.
- Ozturk I and Acaravci A (2010) CO₂ emissions, energy consumption and economic growth in Turkey. *Renewable and Sustainable Energy Reviews* 14: 3220–3225.

- Pao HT and Tsai C-M (2011) Multivariate Granger causality between CO₂ emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy* 36: 685–693.
- Perron P (1989) The great crash, the oil price shock, and the unit root hypothesis. *Econometrica* 57(6): 1361–1401.
- Pesaran HM and Shin Y (1999) An autoregressive distributed lag modelling approach to cointegration analysis. In: *Chapter 11 in econometrics and economic theory in the 20th century the Ragnar Frisch centennial symposium* (ed S Strom), Oslo, Norway 1995. Cambridge: Cambridge University Press, pp.371–413.
- Pesaran HM, Shin Y and Smith RJ (2001) Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics* 16(3): 289–326.
- Phillips PCB and Perron P (1988) Testing for a unit root in time series regression. *Biometrika* 75(2): 335–346.
- Rafiq S, Bloch H and Salim R (2014) Determinants of renewable energy consumption in China and India: A comparative analysis. *Applied Economics* 46(22): 2700–2710.
- Romilly P, Song H and Liu X (2001) Car ownership and use in Britain: a comparison of the empirical results of alternative cointegration estimation methods and forecasts. *Applied Economics* 33(14): 1803–1818.
- Saboori B, Sapri M and bin Baba M (2014) Economic growth, energy consumption and CO₂ emissions in OECD (Organization for Economic Co-operation and Development)'s transport sector: A fully modified bi-directional relationship approach. *Energy* 66: 150–161.
- Shahbaz M, Lean HH and Shabbir MS (2012) Environmental Kuznets curve hypothesis in Pakistan: Cointegration and Granger causality. *Renewable and Sustainable Energy Reviews* 16: 2947–2953.
- Shahbaz M and Lean HH (2012) Does financial development increase energy consumption? The role of industrialization and urbanization in Tunisia. *Energy Policy* 40: 473–479.
- Shin Y, Yu B and Greenwood-Nimmo M (2014) *Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework*. Chapter 9. Springerlink.
- Stern DI (2004) The rise and fall of the environmental Kuznets curve. *World Development* 32: 1419–1439.
- Tang CF (2008) A re-examination of the relationship between electricity consumption and economic growth in Malaysia. *Energy Policy* 36: 3077–3085.
- Wang SS, Zhou DQ, Zhou P and Wang QW (2011) CO₂ emissions, energy consumption and economic growth in China: A panel data analysis. *Energy Policy* 39: 4870–4875.
- Wang Y, Wang Y, Zhou J, et al. (2011) Energy consumption and economic growth in China: A multivariate causality test. *Energy Policy* 39: 4399–4406.
- World Bank (2016) *World Development Indicators (WDI)*. Washington, DC: Author.
- Yalta AT and Cakar H (2012) Energy consumption and economic growth in China: A reconciliation. *Energy Policy* 41: 666–675.