Coal Consumption, Industrial Production and CO2 Emissions in China and India

Shahbaz, Muhammad and Farhani, Sahbi and Ozturk, Ilhan

COMSATS Institute of Information Technology, Lahore Campus, Pakistan, LAMIDED, ISG Sousse, University of Sousse, 4000 Sousse, Tunisia, Faculty of Economics and Administrative Sciences, Cag University, 33800 Mersin, Turkey

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Muhammad Shahbaz
COMSATS Institute of Information Technology, Lahore Campus, Pakistan
Email: shahbazmohd@live.com
Tel.: +92-334-366-4657, Fax: +92-429-920-3100

Sahbi Farhani
LAMIDED, ISG Sousse, University of Sousse, 4000 Sousse, Tunisia
Email: sahbi_1984@yahoo.fr
Tel.: +216-22-833-253

Ilhan Ozturk
Faculty of Economics and Administrative Sciences, Cag University, 33800 Mersin, Turkey
Email: ilhanozturk@cag.edu.tr
Tel.: +90-324-6514828

Abstract: The present study explores the relationship between coal consumption, industrial production and CO_2 emissions in case of China and India for the period of 1971-2011. The structural break unit root test and cointegrating approach have been applied. The direction of causal relationship between the variables is investigated by applying the VECM Granger causality test. Our results validate the presence of cointegration among the series in both countries. We also find the existence of inverted U-shaped curve between industrial production and CO_2 emissions for India but for China it is U-shaped relationship. Coal consumption adds in CO_2 emission. The causality analysis reveals that industrial production and coal consumption Granger cause CO_2 emission in India. In case of China, the feedback effect exists between coal consumption and CO_2 emissions.
Keywords: Coal consumption, Industrial production, CO_2 emissions, China, India

1. Introduction

In the last decade, there has been a remarkable growth in coal demand, which was the largest of all primary energy resources and almost equal to the combined growth in natural gas, oil, nuclear and renewables. The main drivers of the present study were China and India, where coal consumption increased from 720 Mtoe in 2001 to 1676 Mtoe in 2011 for China, and from 145 Mtoe in 2001 to 271 Mtoe in 2011 for India. Driven by rapid economic growth, coal demand has been characterized by boom with rising demand of about 80% between 2000 and 2010. In 2011, coal production reached a record level of 7.678 Mt increasing by 6.6% over 2010. The annual average growth rate of coal production since 1999 was 4.4%. The top five coal producers in 2011 are China, USA, India, Australia and Indonesia. Coal is the back bone of electricity generation worldwide, and has been the fuel underpinning the rapid industrialization of emerging economies. Coal fuels more than 40% of the world's electricity, though this figure is much higher in many countries, such as South Africa (93%), China (79%), India (69%) and the USA (49%) (IEA, 2012; BP, 2012a).

China is the largest coal consumer in the world, accounting for 49.4% (3.12 Gt or 1839.4 Mtoe, excluding Hong Kong) of global total coal consumption in 2011. Over the period of 2011-2030, China forecasts to account for 67% of global coal growth to 2030 and remains the largest coal consumer, increasing its share of global consumption from 48% to 53%. India is currently the fourth largest coal consumer in the world, consuming 295.6 Mtoe of coal in 2011. Coal constituted the largest share (42%) of India's total primary energy consumption in 2009 (BP, 2012b). China and India have recorded very high economic growths within emerging economics in the last decade. This increase resulted in a significant rise in their energy use of total energy consumption, especially increases in the consumption of coal. Unfortunately the increase in coal consumption resulted in an increase in carbon emissions. The increase in industrial value added to GDP per capita, coal consumption per capita and CO_2 emissions per capita in industrial sector can be seen in Figures 1-3.

In case of sustainable development, these countries should reduce coal consumption and increase the proportion of renewable energy sources. Because the fear of climate changes, increasing carbon emissions and applying Kyoto Protocol in the future will limit the coal use in these countries. According to Kyoto Protocol, these countries are required to reduce carbon emissions but unfortunately the carbon emissions have been increased and this increase still continues. Even coal consumption contributes more carbon emissions than other energy sources, it is still most important energy source for the growth of these countries and thus any decrease in coal will effect negatively the development of India and China. Industrial coal consumption from 2008 to 2035 is expected to grow by 67% in China and 94% in India.

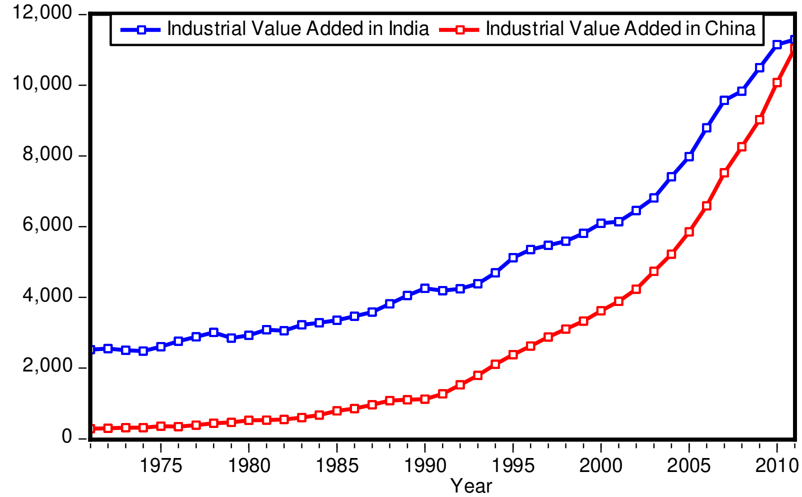

Figure-1. *Real industrial value added per capita in India and China, 1971-2011*

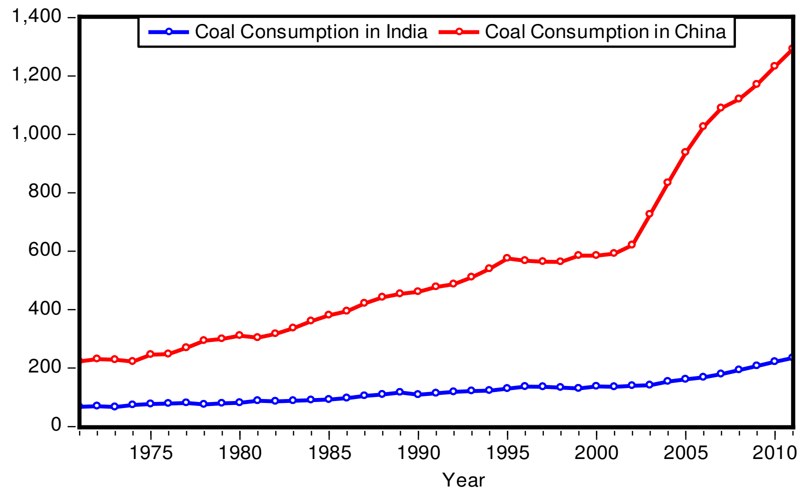

Figure-2. *Industrial coal consumption per capita in India and China, 1971-2011*

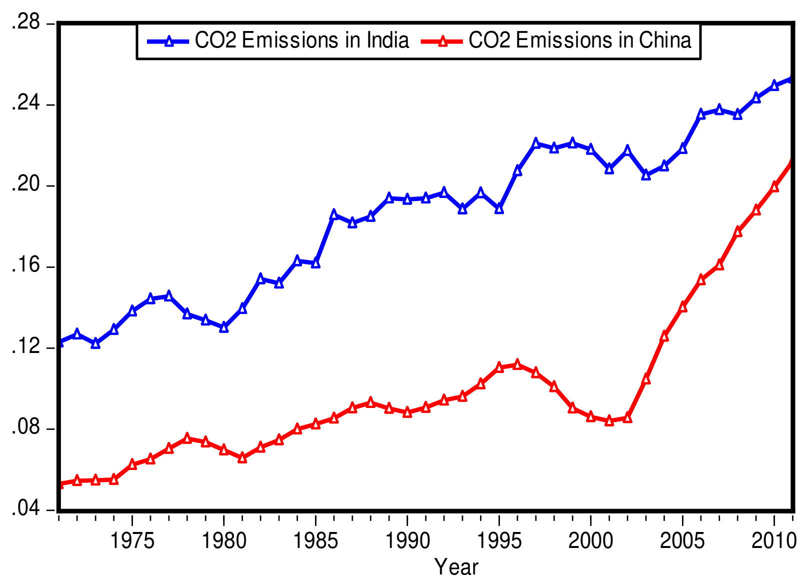

Figure-3. *Industrial CO_2 emissions per capita in India and China, 1971-2011*

There is limited evidence available on analyzing the coal consumption and its implications for industrial production and CO_2 emissions using recent and longer time series data (e.g. 1971-2011) in the existing energy literature. In addition, most of the previous studies analyzing the issues used aggregate energy consumption data and not coal consumption. Thus, this paper will contribute the existing literature to understand the relationship between coal consumption, industrial production and carbon emissions in China and India. In this study, we also use recent datasets (longer time series data from 1971 to 2011) to investigate the issues in both China and India by using Zivot and Andrews (1992) and Clemente et al. (1998) unit root tests to identify structural break(s) and in order to avoid misleading results when data series exhibit shocks. We have also applied the Bayer and Hanck (2013) combined cointegration approach to examine whether cointegration exists. The VECM Granger causality framework is used to detect the direction of causal relationship between the variables.

The remainder of the paper is organized as follows. Section-2 provides a brief summary of literature review. In Section-3 we state data, methodology and empirical results whereas the conclusion and policy implications are presented in Section-4.

2. Literature review

The existing literatures, to our knowledge, revealed that very few studies are available on the issues of coal consumption and its link to economic growth and CO_2 emissions. Except for a few, most of the studies examined the relationship between energy consumption, economic growth and CO_2 emissions. Generally, these literatures tended to examine one of two approaches: i) the relationship between coal consumption and economic growth; and ii) the relationship between coal consumption, economic growth and CO_2 emissions (see Table-1). The next two sub-sections summarize these literatures:

2.1. Economic growth and coal consumption

In the discussion of growth-energy (coal) nexus, the causal relationship is generally synthesized into four testable hypotheses (growth, conservation, feedback and neutrality). First, the growth hypothesis indicates the impact of coal consumption on economic growth directly and/or as a complement to capital and labor. This means that an increase in coal consumption causes an increase in economic growth and also means adoption of energy conservation policies i.e. decrease coal consumption will have negative effect on economic growth. This scenario is studied by Wolde-Rufael (2010) for India and Japan, and proved that industries which use coal are becoming less efficient. Two others works suggested this hypothesis: Sari and Soytas (2004) employed generalized forecast error variance decomposition analysis and found that coal consumption explains up to 8% of the forecast error variance in real GDP for Turkey; and in the case of the US, Ewing et al. (2007) utilized the generalize forecast error variance decomposition analysis and reported that coal consumption explains up to 10% of the forecast error variance of industrial production. Second, the conservation hypothesis indicates that coal consumption is caused by economic growth. This means that an increase in economic growth causes an increase in coal consumption. It implies that adoption of energy conservation policies, i.e. decrease in coal consumption, will not have negative impact on economic growth. This scenario is confirmed by Yang (2000) for Taiwan; Fatai et al. (2004) for Australia; Reynolds and Kolodziej

(2008) for the former Soviet Union; Jinke et al. (2008, 2009) for Japan and China, respectively; Wolde-Rufael (2010) for China and Korea. Third, the feedback hypothesis highlights the presence of bidirectional causal relationship between coal consumption and economic growth. This scenario opens the possibility that energy conservation policies may affect economic growth. This implies that reduction in coal supply will affect economic growth and decline in economic growth will be transmitted back to coal consumption. This hypothesis is proved by Yang (2000) and Lee and Chang (2005) for Taiwan; Yoo (2006) for Korea; Yuan et al. (2008) for China; Li and Leung (2012) for China Coastal and Central regions; Wolde-Rufael (2010) for South Africa and USA; Apergis and Payne (2010a, b) for 15 emerging countries and 25 OECD, respectively. Fourth, the neutrality hypothesis asserts that there is no directly relationship between coal consumption and economic growth or that coal consumption leads to a relatively minor role in economic growth and same is true from opposite side. Under this scenario, energy conservation policies will not affect economic growth. This hypothesis is confirmed by Fatai et al. (2004) for New Zealand; Jinke et al. (2008) for India, South Africa and South Korea; Jinke et al. (2009) for India and South Africa; Ziramba (2009) for South Africa; Ocal et al. (2013) for Turkey.

2.2. CO_2 emissions, economic growth and coal consumption

To our knowledge, until today, only two studies have emphasized the direct relationship between CO_2 emissions, economic growth and coal consumption (Bloch et al. 2012; Govindaraju and Tang, 2013) and only one has emphasized the link between CO_2 emissions, economic growth, coal consumption and trade openness (Tiwari et al. 2013). Bloch et al. (2012) investigated the relationship between CO_2 emissions, income and coal consumption for case of China. They used annual data from 1977 to 2008 and 1965 to 2008 for the supply-side and demand-side analysis, respectively. They also used, in supply-side analysis, output, labor, capital and coal consumption, while in demand-side analysis they used income, coal price, carbon emissions and coal consumption. They confirmed the presence of cointegration between the variables. The causality analysis revealed the unidirectional causality running from coal consumption to output using supply-side model but income Granger causes coal consumption using the demand-side model. The bi-directional causality also exists between coal consumption and energy pollutants. Finally, they concluded that it is very difficult for China to pursue a greenhouse gas abatement policy through reducing coal consumption, but switching to greener energy sources might be a possible alternative in long run.

For the second paper of Govindaraju and Tang (2013), it appears that recent and robust estimation techniques of cointegration have used to provide more conclusive evidence on the nexus of CO_2 emissions, economic growth and coal consumption in China and India over the period of 1965-2009. They found that the variables are cointegrated in case of China but not in India. This shows that the long-run relationship between CO_2 emissions, economic growth and coal consumption only exists in China. The Granger causality analysis indicated the unidirectional causality running from economic growth to CO_2 emissions in China. The feedback effect also exists between economic growth and coal consumption as well as CO_2 emissions and coal consumption. In case of India, causality between economic growth and CO_2 emissions as well as CO_2 emissions and coal consumption are bi-directional in short run. Nonetheless, there is also unidirectional Granger causality running from economic growth to coal consumption.

Table-1. S*ummary of studies on the coal-growth nexus*

Authors	Variables	Period	Countries	Methodology	Results of direction of causality
Yang (2000)	GNP and coal consumption	1954 - 1997	Taiwan	Granger causality	$Y \rightarrow C$
Fatai et al.(2004)	GDP and Aggregate Energy (*AE*: coal, oil, gas, electricity and total final energy consumption)	1960 - 1999	New Zealand, Australia, **India**, Indonesia, The Philippines and Thailand	Engle and Granger OLS approach;Toda and Yamamoto test;andARDL approach	$Y \rightarrow C$ (New Zealand, Australia) $C \rightarrow Y$ (**India**, Indonesia) $Y \leftrightarrow C$ (The Philippines, Thailand)
Sari and Soytas (2004)	GDP, employment and disaggregate categories of energy consumption (coal, oil, hydraulic power, asphaltite, lignite, waste, wood, total energy consumption)	1969 - 1999	Turkey	Developed generalized forecast error variance decomposition technique - VAR	$Y \rightarrow C$ (Coal consumption explains up to 8% of the forecast error variance in real GDP)
Lee and Chang (2005)	GDP and Aggregate Energy (*AE*: coal, oil, gas, electricity and total energy consumption)	1954 - 2003	Taiwan	unit root tests and cointegration tests allowing structural breaks	$Y \leftrightarrow C$
Yoo(2006)	GDP and coal consumption	1968 - 2002	Korea	Engle-Granger; Johansen-Juselius;and Granger causality–ECM	$Y \leftrightarrow C$
Ewing et al.(2007)	Industrial production index, employment, total energy consumption, total renewable energy, coal, fossil fuels, conventional hydroelectric power, solar energy, wind energy, natural gas, wood, alcohol, geothermal, and waste consumption	2001:1 - 2005:6 (Monthly data)	USA	Generalized variance decomposition - VAR	Unexpected shocks to coal have a high impact on the variation of output
Reynolds and Kolodziej (2008)	GNP, oil, coal and natural gas consumption	1987 - 1996	Former Soviet Union (FSU)	Granger causality and multi-cycle Hubbert curve	$C \rightarrow Y$
Jinke et al. (2008)	GDP and coal consumption	1980 - 2005	OECD countries (USA, Japan and South Korea) and non-OECD countries (**China**, **India** and South Africa)	Granger causality and cointegration	$Y \rightarrow C$ (Japan,**China**) $Y \not\leftrightarrow C$ (**India**, South Korea and South Africa) The series are not cointegrated in USA.
Yuan et al. (2008)	Output and aggregated total energy and disaggregated energy (coal, oil and electricity consumption)	1963 - 2005	**China**	Johansen cointegration technique; VEC specification	$Y \rightarrow C$
Jinke et al. (2009)	GDP and coal consumption	1980 - 2005	Developed countries (USA,	Granger causality and	$Y \rightarrow C$ (Japan,**China**)

			and Japan) and developing countries (**China**, **India** and South Africa)	cointegration	$Y \nleftrightarrow C$ (**India**and South Africa) The series are not cointegrated in USA.
Ziramba (2009)	Industrial output, employment and disaggregate energy consumption (coal, oil and electricity consumption)	1980 - 2005	South Africa	Toda and Yamamoto test - Engle and Granger approach	$Y \nleftrightarrow C$
Apergis and Payne (2010a)	GDP, coal consumption, capital, and labor	1980 - 2006	15 emerging market economies	Panel cointegration tests and panel error correction model	$Y \leftrightarrow C$
Apergis and Payne (2010b)	GDP, coal consumption, capital, and labor	1980 - 2005	25 OECD countries	Panel cointegration tests and panel error correction model	$Y \leftrightarrow C$
Wolde-Rufael (2010)	GDP, coal consumption, capital, and labor	1965 - 2005	Six major coal consuming countries (**India**, Japan, **China**, South Korea, South Africa and USA)	VAR - Toda and Yamamoto test - Engle and Granger approach	$C \rightarrow Y$ (**India**, Japan) $Y \rightarrow C$ (**China**, South Korea) $Y \leftrightarrow C$ (South Africa,USA)
Bloch et al. (2012)	*Supply-side* analysis: Output, capital, labor, coal consumption *Demand-side*analysis:Output, coal consumption, coal price and CO_2 emissions	*Supply-side*: 1977 - 2008 *Demand-side*: 1965 - 2008	**China**	Cointegration and vector error correction modeling	*Supply-side* analysis: $C \rightarrow Y$ *Demand-side*analysis: $Y \rightarrow C$, $C \leftrightarrow CO_2$
Li and Leung (2012)	GDP and coal consumption	1985 - 2008	Coastal, Central and Western regions **of China**	panel data techniques	$Y \leftrightarrow C$ (Coastal and Central regions) $Y \rightarrow C$ (Western region)
Govindaraju and Tang (2013)	GDP, coal consumption and CO_2 emissions	1965 - 2009	**China** and **India**		**China**: $Y \leftrightarrow C$; $C \leftrightarrow CO_2$ **India**: $C \leftrightarrow CO_2$; $Y \rightarrow C$
Tiwari et al. (2013)	Real GDP, coal consumption, trade openness and CO_2 emissions	1966-2011	**India**	ARDL Bounds testing approach and VECM Granger causality test	$Y \leftrightarrow C$; $C \leftrightarrow CO_2$
Ocal et al. (2013)	Real GDP, coal consumption, capital and labor force	1980-2006	Turkey	Asymmetric causality	$Y \nleftrightarrow C$

Note. C and Y represent coal consumption and economic growth (GDP, GNP, output, industrial production, income, etc.), respectively.
$\rightarrow$, $\leftrightarrow$ and $\nleftrightarrow$ represent unidirectional causality, bi-directional causality, and neutral causality, respectively.

The policy message is clear for both China and India. China should be cautious in implementing any conservation policy while India should implement the policy without a destabilization of a long run economic growth. As a whole, China may have to put in more effort to devise alternative choices of policy options than India. Since coal consumption impacts CO_2 emissions and economic growth in long run, so any coal conservation policy might reduce CO_2 emissions but has negative consequences on economic growth in China. Since China's electricity generation is mostly from coal, any reduction in coal consumption will adversely affect electricity supply. In this case, Chinese government has to devise policies to improve the efficiency options to increase GDP-coal intensity. In this way, China will be able to reduce CO_2 emissions without any adverse effect on economic growth. Another viable policy option is to increase the consumption of renewable energy. With respect to this, investment and institutional arrangements should be intensified to speed up the development of renewable energy sectors (Govindaraju and Tang, 2013).

Tiwari et al. (2013) also investigated the relationship between coal consumption, economic growth, trade openness and CO_2 emissions using data over the period of 1966-2011. They found that the variables are cointegrated for long run relationship between the variables. Their analysis revealed that the relationship between economic growth and CO_2 emissions is nonlinear i.e. inverted U-shaped. This confirms the presence of environmental Kuznets curve in India. Furthermore, coal consumption adds in CO_2 emissions. The causality analysis reported the bidirectional causality relationship between economic growth and CO_2 emissions and same inference is drawn between coal consumption and CO_2emissions.

3. Data, methodology and empirical results

3.1. Data and model specification

Following the existing literatures on environmental economic, economic growth and energy consumption are two main determinants of CO_2 emissions (e.g. Ang, 2007; Apergis and Payne, 2009, 2010c; Lean and Smyth, 2010; and Arouri et al. 2012). More specifically, the EKC hypothesis is subject to indicate that the relationship between CO_2 emissions and economic growth is non-linear and should be in the form of inverted U-shaped relationship where as the inclusion of energy into the relationship as a means to circumvent omitted variable bias. Empirically, we modify the empirical framework of Govindaraju and Tang (2013) and Kanjilal and Ghosh (2013) and its aim consists to examine the relationship between CO_2 emissions, industrial production and coal consumption (as a proxy for energy consumption) in case of China and India. Hence, our log-quadratic regression model can be expressed as below:

$$\ln E_t = \alpha_0 + \alpha_1 . \ln I_t + \alpha_2 . \ln I_t^2 + \alpha_3 . \ln C_t + \mu_t \quad (1)$$

Where $\ln E_t$, $\ln I_t$ and $\ln C_t$ are natural log of industrial CO_2 emissions per capita (measured in metric tons), natural log of industrial real output per capita (measured using real industrial value added per capita in constant 2005 US$), and natural log of industrial coal consumption per capita (measured in million tons of oil equivalent, Mtoe) respectively. This study covers the annual sample period 1971-2011 for China and India. This dataset is collected from the *World Bank Development Indicators* (CD-ROM, 2012) and the *Review of World Energy* (2012). In the light of above Eq. (1), α_0, α_1, α_2 and α_3 indicate the time-invariant constant and the long-run elasticities of CO_2 emissions ($\ln E_t$) function with respect to industrial real output ($\ln I_t$), squared of industrial real output ($\ln I_t^2$), and industrial coal consumption ($\ln C_t$), respectively. The disturbance term μ_t is assumed to be normally distributed and white noise. As for the expected signs in Eq. (1), one would expect that the sign of α_1 is expected to be positive whereas a negative sign is expected for α_2 for the EKC hypothesis to be true. The sign α_3 is expected to be positive because more energy consumption can increase the scale of an economy and stimulate CO_2 emissions.

3.2. Structural break(s) unit root tests

Prior to testing for cointegration, we check for stationarity of each series. The study period is characterized by major changes in the global landscape which can potentially cause structural breaks. In fact, traditional unit root tests such as ADF (Dickey and Fuller, 1979), PP (Phillip and Perron, 1988), DF-GLS (Elliott et al. 1996) and Ng-Perron (Ng and Perron, 2001) are used to find out integrating order of the variables. However, these tests give misleading results when data series exhibits shocks[1]. It is also pointed by Baum, (2004) that empirical evidence on order of integration of the variable by ADF, PP, DF-GLS and Ng-Perron is not reliable. Therefore, attempts have been made to develop test of unit root which incorporates presence of structural breaks in the null of unit root hypothesis. There are four recent studies namely Datta (2011), Dholakia and Sapre (2011), Govindaraju and Tang (2013), and Tiwari et al. (2013) in Indian economy, and two recent studies namely Jayanthakumaran et al. (2012) and Kanjilal and Ghosh (2013) in both Chinese and Indian economies pointing out structural changes in different sectors and overall GDP which motivates and also justifies utilization of unit root test that incorporates structural breaks. At this level, we start applying the Zivot and Andrews (1992) unit root test to identify single unknown structural break and Clemente et al. (1998) unit root test to identify two unknown structural breaks arising in the series. The Clemente et al. (1998) test has more power compared to the Zivot and Andrews (1992) test (Shahbaz et al. 2013a, b, c).

For robustness check, we perform the results of two unit root tests in Table-2 and Table-3. We find that there is structural break(s) in the variables and that strengthen the use of non-linear model for testing the presence of EKC. Moreover, the use of Zivot and Andrews (1992) and Clemente et al. (1998) unit root tests also indicate that the variables are integrated of order 1.

Table-2. *Zivot–Andrews structural break trended unit root test results*

	At level		*At first difference*	
	T-statistics	*Time break*	*T-statistics*	*Time break*
China				
ln E	-2.384 (2)	2007	-4.434** (3)	2001
ln I	-0.853 (3)	1990	-4.786** (4)	1989
ln C	-2.216 (3)	2001	-4.947** (3)	2001
India				
ln E	-2.599 (6)	1979	-5.280** (3)	1985
ln I	0.467 (2)	2001	-4.879** (2)	2002

[1] See Tiwari and Shahbaz (2013)

ln C	-0.981 (3)	2002	-7.415* (3)	2002

Note. Lag length of variables is shown in small parentheses.
* and ** indicate significance at 1% and 5% level, respectively.

Table-3. *Clemente–Montanes–Reyes structural breaks trended unit root test results*

	At level			*At first difference*		
	T-statistics	*Time break 1*	*Time break 2*	*T-statistics*	*Time break 1*	*Time break 2*
China						
ln E	-4.893 (3)	1980	2001	-7.251* (4)	1996	2001
ln I	-4.733 (4)	1982	2001	-6.571* (5)	1994	2001
ln C	-1.551 (4)	1982	1990	-6.554* (6)	1975	1989
India						
ln E	-2.552 (4)	1984	1994	-6.026** (5)	1979	1985
ln I	-0.392 (5)	1992	2002	-6.041** (8)	1978	2002
ln C	-2.063 (5)	1984	2002	-7.935* (6)	1995	2002

Note. Lag length of variables is shown in small parentheses.
* and ** indicate significance at 1% and 5% level, respectively.

3.3. Bayer-Hanck cointegration test

Engle and Granger (EG, 1987) proposed the first version of cointegration test based on the estimated residuals of a long run regression model. This method was then termed as the residuals based test for cointegration. After a decade, various cointegration tests were developed such as the system-based test of Johansen (J, 1988), the ECM-based F-test of Boswijk (B, 1994) and the ECM-based t-test of Banerjee et al. (BDM, 1998). Unfortunately, different cointegration tests might suggest different conclusions because no one cointegration test was perfect and completely robust in all applications (Elliott et al. 2005). This also implies that all these cointegration approaches have different theoretical backgrounds and produce conflicting results, and that the power of ranking cointegration approaches is sensitive with the value of nuisance estimators (Pesavento, 2004). To enhance the power of the cointegration tests, this study uses the newly-developed cointegration test suggested by Bayer and Hanck (2013) to check the presence of cointegrating relationship between CO_2 emissions and its determinants in China and India. A unique aspect of this new cointegration test is, it allows us to combine various individual cointegration test results to provide a more conclusive finding. With respect to this, Bayer and Hanck (2013) proposed to combine the computed significance level (p-values) of the individual cointegration test with the following Fisher's formulas:

$$EG-J=-2\left[\ln(p_{EG})+\ln(p_J)\right] \tag{2}$$

$$EG-J-B-BDM=-2\left[\ln(p_{EG})+\ln(P_J)+\ln(P_B)+\ln(P_{BDM})\right] \tag{3}$$

where the p-values of various individual cointegration tests such as Engle-Granger (EG, 1987); Johansen (J, 1988); Boswijik (B, 1994) and, Banerjee et al. (BDM, 1998) are shown by p_{EG}, p_J, p_B and p_{BDM} respectively. If the calculated Fisher statistics exceed the critical values provided by Bayer and Hanck (2013), the null hypothesis of no cointegration can be rejected.

Table-4. *Bayer-Hanck cointegration test results*

Model Specification	*Fisher statistics*		*Cointegration*
	EG –J	*EG –J –B–BDM*	
China			
$E_t = f(I_t, I_t^2, C_t)$	11.236**	28.744**	Yes
$I_t = f(E_t, I_t^2, C_t)$	9.806	13.550	Yes
$I_t^2 = f(E_t, I_t, C_t)$	8.098	20.241	Yes
$C_t = f(E_t, I_t, I_t^2)$	8.424**	20.174***	Yes
India			
$E_t = f(I_t, I_t^2, C_t)$	11.758**	28.494**	Yes
$I_t = f(E_t, I_t^2, C_t)$	6.890	9.653	No
$I_t^2 = f(E_t, I_t, C_t)$	4.782	12.712	No
$C_t = f(E_t, I_t, I_t^2)$	4.851	13.135	No
Significance level	*Critical values*		
1 %	16.26	31.17	
5 %	10.64	20.49	
10 %	8.363	16.10	

Note. **and *** represent significance at 5 and 10% level, respectively.

Empirically, as our structural break(s) unit root tests results reveal that all variables follow the I(1) process, we can proceed to implement the combined cointegration tests proposed by Bayer and Hanck (2013). Table-4 exhibits the results of combined cointegration tests, namely EG–J and EG–J–B–BDM. Given the cointegration test results are sensitive to the choice of endogenous variable; we perform the combined cointegration tests in four models. For the case of China, the Fisher statistics for EG–JOH and EG–JOH–BO–BDM tests are greater than the 5% and 10% critical bounds values regardless of which variable is employed. Therefore, both EG–JOH and EG–JOH–BO–BDM tests consistently reject the null hypothesis of no cointegrating relationship between the variables. However, the combined cointegration results for case of India totally contradict with the findings in China's case except for case of CO_2 emissions as dependent variable. Both combined cointegration tests fail to reject the null hypothesis of no cointegration. Therefore, we surmise that there is a long run equilibrium relationship between coal consumption, industrial growth and CO_2 emissions in China and India. Our findings are consistent in case of China (e.g. Li et al. 2011; Wang et al. 2011; Li and Leung, 2012; Govindaraju and Tang, 2013) and same is true for India's case (e.g. Ghosh, 2010; Govindaraju and Tang, 2013) on the presence of cointegration for India, too.

3.4. Long- and short-run results

Table-5 provides the long-and-short runs results of the country-by-country. The estimated coefficients from the long-and-short runs cointegration relationship can be interpreted as long run and short run elasticities.

Table-5. *Long- and short-runs results*

Dependent variable = $\ln E_t$				
China	*Long Run Analysis*		*Short Run Analysis*	
	Coefficient	T-Statistic	Coefficient	T-Statistic
Constant	-3.469*	-4.640	-0.017	-1.230
$\ln I_t$	-0.375*	-3.831	-0.301	-0.963
$\ln I_t^2$	0.013**	2.070	1.648	0.921
$\ln C_t$	0.727*	5.624	1.019*	5.561
ECM_{t-1}			-0.485*	-2.755
Diagnostic tests	R^2	0.9858	R^2	0.7606
	F-statistic	609.85*	*F-statistic*	20.975
India	*Long Run Analysis*		*Short Run Analysis*	
	Coefficient	T-Statistic	Coefficient	T-Statistic
Constant	-10.11*	-3.079	-0.004	-0.3414
$\ln I_t$	1.763**	2.559	0.625	0.2486
$\ln I_t^2$	-0.108*	-2.779	-0.039	-0.2675
$\ln C_t$	0.443*	4.057	0.382**	-2.1978
ECM_{t-1}			-0.116*	-4.1557
Diagnostic tests	R^2	0.9722	R^2	0.4113
	F-statistic	306.18*	*F-statistic*	4.6116

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

In long-run, the coefficients are quite significant at the 5% level. For Chinese case, the coefficients are –0.375, 0.013 and 0.727 for $\ln I_t$, $\ln I_t^2$ and $\ln C_t$ respectively. This means that the elasticity of CO_2 emissions with respect to the industrial production is –0.375 + $0.026 \ln I_t$ (there is an U-shaped curve between CO_2 emissions and industrial production), and a 1% increase in coal consumption increases CO_2 emissions by 0.727%, all else is same. Moreover, the high value of R^2 shows that the adjustment of Eq. (1) is extremely good for case of China ($R^2 = 0.9858 \rightarrow 1$). In addition, the F-statistic which measures the joint significance of all regressors in the models is statistically significant at 1% level. For Indian case, the coefficients are 1.763, –0.108 and 0.443 for $\ln I_t$, $\ln I_t^2$ and $\ln C_t$ respectively. This means that the elasticity of CO_2 emissions with respect to the industrial production is 1.763 – $0.216 \ln I_t$ (there is an inverted U-shaped curve between CO_2 emissions and industrial production), and a 1% increase in coal consumption increases CO_2 emissions by 0.443% by keeping other things constant. Moreover, the high value of R^2 shows that the adjustment of Eq. (1) is extremely good for case of India ($R^2 = 0.9722 \rightarrow 1$), and the F-statistic is also statistically significant at 1% level.

In short-run, the coefficients are quite significant only for case of coal consumption. In general, the short-run impact of independent variables including lagged error term, ECM_{t-1}, is used with applying OLS version. This term indicates the speed of adjustment from short-run towards long-run equilibrium path with negative sign. It is suggested by Banerjee et al. (1998) that significance of lagged error term further validates the established long-run relationship between the variables. Empirically, our results indicate that coefficients of ECM_{t-1} significant at 1% level of significance and they are equal to –0.485 and –0.116 for China and India, respectively. For the short-run, diagnostic tests indicate that the adjustment of Eq.1 is good for case of China and not for India's case. In addition, the F-statistics are also statistically significant for two cases.

3.5. Granger causality test results

A vector error correction model (VECM) is estimated to perform Granger-causality test. This method is followed by the two steps of Engle and Granger (1987) and employed to investigate the long-run and short-run dynamic causal relationships. The first step estimates the long-run parameters in Eq. (4) in order to obtain the residuals corresponding to the deviation from equilibrium. The second step estimates the parameters related to the short-run adjustment. The resulting equations are used in conjunction with Granger causality testing:

$$(1-L)\begin{bmatrix}\ln E_t\\ \ln I_t\\ \ln C_t\end{bmatrix}=\begin{bmatrix}\phi_{1t}\\ \phi_{2t}\\ \phi_{3t}\end{bmatrix}+\sum_{c=1}^{d}(1-L)\begin{bmatrix}\theta_{1,1,c} & \theta_{1,2,c} & \theta_{1,3,c}\\ \theta_{2,1,c} & \theta_{2,2,c} & \theta_{2,3,c}\\ \theta_{3,1,c} & \theta_{3,2,c} & \theta_{3,3,c}\end{bmatrix}.\begin{bmatrix}\ln E_{t-1}\\ \ln I_{t-1}\\ \ln C_{t-1}\end{bmatrix}+\begin{bmatrix}\lambda_1\\ \lambda_2\\ \lambda_3\end{bmatrix}.ECT_{t-1}+\begin{bmatrix}\xi_{1,t}\\ \xi_{2,t}\\ \xi_{3,t}\end{bmatrix} \quad (4)$$

where, ϕ_j (j=1,2,3) represents the time-invariant constant; c (c=1,...,d) is the optimal lag length determined by the minimization of AIC criterion; (1 − L) is the lag operator; ECT_{t-1} is the lagged residual obtained from the long run relationships of Eq. (1), λ_j (j=1,2,3) is the adjustment coefficient, and $\xi_{j,t}$ (j=1,2,3) is the disturbance term assumed to be uncorrelated with zero means.

Table-6. *Granger causality test results*

Dependent Variable	*F-statistics* (Probabilities)			ECT_{t-1} [t-stat]
	$\Delta \ln E_t$	$\Delta \ln I_t (\Delta \ln I_t^2)$	$\Delta \ln C_t$	
China				
$\Delta \ln E_t$	#	0.0166 (0.9885)	3.8888** (0.0384)	-0.6624* [-3.4121]
$\Delta \ln I_t (\Delta \ln I_t^2)$	0.5645 (0.5744)	#	1.8219 (0.1786)	-1.5823 [-1.0671]
$\Delta \ln C_t$	16.2172* (0.0000)	0.1913 (0.8228)	#	-0.2294** [-2.2308]
India				
$\Delta \ln E_t$	#	2.1745 (0.1312)	15.9708* (0.0015)	-0.1026* [-6.0706]
$\Delta \ln I_t (\Delta \ln I_t^2)$	0.7990 (0.4588)	#	1.1904 (0.3176)	-1.5823 [-0.0322]
$\Delta \ln C_t$	2.2568***	3.6030**	#	-0.6177

	(0.0520)	(0.0392)	[-0.1901]

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

Table-6 summarizes the results of long-run and short-run Granger causality. According to the coefficient on the lagged error correction term, there exists a long-run relationship among the variables in the form of Eq.(1) as the error-correction term is statistically significant, which also confirms the estimation results. In long run, industrial production and coal consumption cause CO_2 emissions for case of China. In this case, there also exists another long-run Granger causality which runs interactively through the error-correction terms from CO_2 emissions Granger cause coal consumption and coal consumption Granger causes CO_2 emissions. The unidirectional causality is found running from industrial growth CO_2 emissions and coal consumption. But in short-run, the findings reveal a bidirectional Granger causality relationship CO_2 emissions and coal consumption. In case of India, there exists unidirectional Granger causality is found running from economic growth and coal consumption to CO_2 emissions in long run. But in short run, the feedback effect exists between CO_2 emissions and coal consumption. The unidirectional Granger causality is also exists running from industrial production to coal consumption.

In addition, for case of China, our results support Bloch et al. (2012) that suggested the bidirectional causality between CO_2 emissions and coal consumption and contradictory with Li and Leung (2012) who reported bidirectional causality between industrial production and coal consumption. Similarly, our findings also support Chang (2010) and Wang et al. (2011) who found that industrial production Granger causes CO_2 emissions. Nevertheless, when comparing with those studies that use aggregate energy consumption data, our study seems to support some of the claims (e.g. Wang et al. 2011; Govindaraju and Tang, 2013) and contradict with (e.g. Li et al. 2008; Wolde-Rufael, 2010) especially with regards to short run causality between energy and industrial production, CO2 emissions and energy as well as for long run causality between industrial production and CO_2 emissions. This may be due to the fact that coal represents a larger energy mix of the entire energy consumption and their influences are well captured even if aggregate energy consumption data is used (Govindaraju and Tang, 2013). In general, there is some form of consensus on the direction of causality between CO_2 emissions, coal consumption and industrial production when comparing to the previous studies. This consensus provides policy makers to further validate the direction of causality between CO_2 emissions, coal consumption and industrial production in China for future energy planning.

Similarly, in case of India, our results support Alam's et al. (2011) findings that industrial production Granger causes coal consumption. However, our findings contradictory with Wolde-Rufael (2010) who found unidirectional causality running from coal consumption to economic growth, and Ghosh (2010) who reported the bidirectional causality between CO_2 emissions and economic growth. Govindaraju and Tang (2013) explain this difference between findings by the application of cross-country and panel data analysis. The preferred country specific analysis in this study captures and accounts for the complexity of economic environment and histories of energy development in China and India respectively, of which panel analysis is unable to capture.

4. Conclusion and policy implications

The present study investigates the relationship between CO_2 emissions, industrial production and coal consumption using time series data over the period 1971–2011 in cases of China and India. To test the stationary properties of the data, we used Zivot and Andrews (1992) unit root test to identify single unknown structural break and Clemente et al. (1998) unit root test to identify two unknown structural breaks, and which incorporates endogenously determined structural break in the series while a log-quadratic regression model is expressed for relationship between variables. The results of Zivot and Andrews (1992) and Clemente et al. (1998) unit root tests show that non-stationary process is found in all series at level with intercept and trend but variables are found to be stationary at 1st difference. This means that all variables are integrated of order 1 i.e. I(1). To enhance the power of the cointegration tests, we used newly-developed cointegration test suggested by Bayer and Hanck (2013) to check the presence of cointegrating relationship between CO_2 emissions, industrial growth and coal consumption. With respect to this, we found the presence of cointegration between variables.

This paper also fills the gap in existing energy literature of EKC hypothesis. This hypothesis has been established for the case of India, but not for China. For Chinese case, the coefficients are –0.375, 0.013 and 0.727 for industrial production, squared industrial production and coal consumption, respectively. This means that there is a U-shaped curve between CO_2 emissions and industrial production, and a 1% increase in coal consumption increases CO_2 emissions by 0.727%; whereas, for Indian case, the coefficients are 1.763, –0.108 and 0.443 for industrial production, squared industrial production and coal consumption, respectively. This means that there is an inverted U-shaped curve between CO_2 emissions and industrial production, and a 1% increase in coal consumption increases CO_2 emissions by 0.443%. Since the variables are cointegrated, the direction of Granger causality proved that industrial production and coal consumption Granger cause CO_2 emissions for case of China in long-run. In this case, there also exists another long-run Granger causality which runs interactively through the error-correction terms from CO_2 emissions and industrial production to coal consumption. But in short-run, the findings reveal a bidirectionasl Granger causality relationship between CO_2 emissions and coal consumption; whereas for case of India, there exists only one long-run Granger causality which runs interactively through the error-correction terms from industrial production and coal consumption Granger causes CO_2 emissions in long run. But in short-run, the findings reveal a bidirectional Granger causality relationship between CO_2 emissions and coal consumption, and unidirectional Granger causality relationship runs from industrial production to coal consumption.

Due to the importance of coal in China and India, any reduction in coal consumption will negatively affect their economic growth as well as electricity supply. Because most of the China's and India's electricity generation (it is 79% in China and 69% in India) is provided by coal. In addition, the coal consumption is the main factor of increasing CO_2 emissions in these countries. Thus, to reduce CO_2 emissions both countries should improve coal utilization efficiency and increase the usage of renewable energy sources for reducing the coal consumption without any negative effects on their economic growths.

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