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Nguyen, Duc Khuong and Sévi, Benoît and Sjö, Bo and
Salah Uddin, Gazi

IPAG Business School, Paris, France, Université de Nantes, Nantes,
France, Linköping University, Linköping, Sweden, Linköping
University, Linköping, Sweden

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The role of trade openness and investment in examining the energy-growth-pollution nexus: Empirical evidence for China and India

Duc Khuong Nguyen[a,*], Benoît Sévi[b], Bo Sjö[c], Gazi Salah Uddin[c]

[a] IPAG Business School, Paris, France
[b] Université de Nantes, Nantes, France
[c] Linköping University, Linköping, Sweden

Abstract

Most of the existing literature dealing with the relationship between carbon emissions, energy consumption and economic growth either suffers from ignoring relevant variables such as trade openness or investment, or suffers from using econometric methods that are unable to distinguish between short and long-term causality and are not robust to the degree of integration of time series used for the analysis. This paper suggests using the autoregressive distributed lag (ARDL) approach along with additional explanatory variables such as measures of trade and investment to shed a new light on the link between emissions, energy consumption and income in the two largest and energy-intensive developing economies: China and India. Our results, over the 1971-2009 period, provide evidence that investment plays a major role in shaping the relationship between carbon emissions, energy consumption and income in China while this is not the case in India. Furthermore, trade openness is found to play a key function in the short-term in China but does not contribute to the emissions-energy-growth scenario in India.

Keywords: energy, carbon emissions, income, ARDL approach, India, China
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[*] *Corresponding author*: 184, Boulevard Saint-Germain, 75006 Paris, France.
Email addresses: D.K. Nguyen (duc.nguyen@ipag.fr), G. Salah Uddin (gazi.salah.uddin@liu.se), B. Sévi (benoit.sevi@gmail.com), B. Sjö (bo.sjo@liu.se)

1. Introduction

This paper fills a gap in the economic literature as it looks, for the first time, to the relationship between carbon emissions, energy consumption and income for the two largest and energy-intensive developing economies in the world – China and India – using a robust econometric methodology and controlling for both trade openness and investment level. More specifically, the autoregressive distributed lag (ARDL) model we rely on is able to analyze both the short-run and the long-run causal relationships between emissions, energy and economic growth while taking into account the order of integration of the time series under investigation. In addition, we include trade openness and investment level in our analysis thereby dealing with the so-called "omitted-variable-bias" often thought as responsible of mixed empirical evidence in existing studies (see, e.g., the discussion in Dinda (2004) and Huang et al. (2008)). Conjugating the ARDL method and control variables makes our analysis innovative with respect to the current literature.

Our study is also motivated by the fact that over the past two decades, climate change due to global warming has risen in prominence as one of the most significant challenges facing the world. Factors such as increased population, rapid economic growth in developing countries, and lifestyle changes are driving the global increase in atmospheric carbon dioxide (CO_2) concentrations. For instance, CO_2 emissions are recognized as a major component of greenhouse gases (GHGs) which cause the global warming. Efforts by governments worldwide have been made to address these challenging issues of climate change, among which the Kyoto Protocol, signed in 1997 within the United Nations Framework Convention on Climate Change (UNFCCC) has been a first-ever important initiative. The Protocol aims at reducing the GHG emissions of 39 industrialized countries and the European Union by around 5% below the 1990 levels by 2012. By 2009, 187 countries have signed and ratified the Kyoto Protocol. Among recent developments, the climate change conference in Durban (South Africa) resulted in a legally binding agreement to establish a new treaty on limiting CO_2 emissions, to be prepared by 2015 and to take effect in 2020.

While reducing CO_2 emissions may not appear to be constraining for their economic growth thanks to their ability to improve energy efficiency and resources to develop clean technology, emerging and developing countries face a compromising situation as energy is intensively consumed to support their economic growth and development program (Han and Chatterjee (1997). This is particularly true for China and India, the two largest countries in the world, which have experienced high rates of economic growth in recent years. Indeed, both economies have witnessed rapid economic growth throughout the 1990s and 2000s with annual average growth rate around 10% for both economies. China has recently overtaken the U.S. as the world's largest economy and by 2020 India is projected to become the world's third largest economy.

The main problem faced by China and India is that their high rates of economic growth have been associated with high levels of energy use and carbon dioxide emissions. This is mainly due to the structure of their economy which is not, in the current state, highly service-oriented. For the 2005-2009 period, energy consumption in China and India grew by an annual average rate of 11% and 4%, respectively (Diener and Frank (2010)). In 2006, they also contributed to 21.5% (1st largest) and 5.3% (5th largest) of global CO_2 emissions, respectively, indicating the weight of their emissions. In India, energy supply is expected to increase by a factor of 3 to 4 by 2031 based on current trends and 2003 as a base year, with coal being the dominant source of energy due to its affordability and availability.[1] Similarly, the U.S. Energy Information Agency (EIA) projects that the installed coal-fired generating capacity in China will double in level from 2008 levels by 2035.[2] In summary, to maintain high economic growth rates, developing economies heavily rely on energy consumption and are likely to generate more and more carbon emissions. In this context, enhancing our understanding of the intimate relationship between carbon emissions, energy consumption and economic growth is crucial to provide policy-makers with necessary tools to curb national environmental policy orientations and to foster policy coordination at the international level.

The view that future economic growth in developing countries will increase emissions level is, however, challenged by economic theory. The pioneering work of Kuznets (1955), which originally hypothesized the existence of an inverted U-shaped relationship between economic growth and income inequality, has been adapted to test a comparable relationship between economic growth and environmental quality.[3] More precisely, the Environmental Kuznets Curve (EKC) hypothesis states that environmental degradation will initially increase as per capita income rises. At some point, however, the degradation will begin to decline, thereby forming an inverted U-shaped curve. In the context of carbon emissions, this indicates that emissions might decrease as further economic development occurs and more resources should be allocated to fight against pollution through the development of energy-efficient technologies and renewable (zero-pollution) energy sources.

There is a huge empirical literature testing for a possible EKC[4] but existing work leads to mixed and somewhat contradictory results. Studies make use of a large set of pollutants and data sources for a single country or a set of countries. Importantly, a central distinction exists between studies looking at a single country and studies examining a panel of countries. Our choice to limit our analysis to two countries is in line with recent research which criticizes the panel data analysis of the EKC (see Dinda (2004), Stern (2004) or Wagner (2008), among others) in light of the heterogeneity of the economic development process for different countries or a set of regions as in the early, and seminal, contribution of Grossman and Krueger (1995). For instance, Stern (2004) note that despite the EKC is an empirical phenomenon, the econometric methodology used to investigate this issue is, most of the time, called into question. Moreover, the empirical validity of the EKC is itself debatable as several variables may play a role in shaping the relationship between carbon emissions and economic growth and these variables may be different for the various countries analyzed. So far, the literature has considered energy consumption as a major factor impacting the EKC but other variables have been added such as industry structure, demographic structure, labor force, capital and foreign trade, among others.

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[1] Integrated Energy Policy, Planning Commission of India, http://planningcommission.nic.in/reports/genrep/rep_intengy.pdf, accessed 16 July 2012.

[2] International Energy Outlook 2011 Highlights, US EIA, http://www.eia.gov/forecasts/ieo/more_highlights.cfm#world, Accessed 16 July 2012.

[3] Dinda (2005) and Kijima et al. (2010) provide excellent surveys of theoretical developments around the environmental Kuznets curve concept and its microeconomic underpinnings. Dasgupta et al. (2002) provide an interesting view on assumptions and implications of the existence of an EKC.

[4] See Stern (2004), Dinda (2004), Dinda and Coondo (2006), Carson (2010) and references therein for an excellent presentation and discussion of existing studies.

This paper deals with both the robustness of the econometric approach and the "omitted-variable-bias" issues by considering the global relationship between carbon emissions, energy consumption, income, trade openness and investment. We do so in an econometric model allowing for short and long-run effects where all variables are considered as endogenous and where variables can indifferently be integrated of order one or zero. To our best knowledge, our paper is the first one making use of this methodology for both China and India over such an extended time period (1971-2009) and controlling for variables such as foreign trade and investment, thereby allowing for a rigorous comparison with existing studies including additional variables to the standard emissions-energy-growth nexus.

Our main findings are as follows: over the period 1971-2009, we obtain support for the major role played by investment in shaping the relationship between carbon emissions, energy consumption and income in China but not for India. Moreover, trade openness is found to play a key role in the short-term in China but does not contribute to the emissions-energy-growth scenario in India.

The remainder of this paper is structured as follows: the next section provides a review of the recent literature dealing with the emissions-energy-growth nexus and further extensions where additional variables have been considered in the empirical analysis. Section 3 describes the econometric approach. In Section 4, we first present the data and then provide the empirical results. Section 5 summarizes our results, discusses policy implications and suggests new avenues for future research.

2. Relevant literature

2.1 *Empirical evidence for China and India*

The analysis of the relationship between carbon emissions, energy consumption and economic growth emerges as the conjunction of contributions in two different research areas. In the first one, researchers have attempted to investigate the existence of an EKC in various contexts (see Grossman and Krueger (1991, 1995), Shafik (1994), Dinda and Coondoo (2006), Heil and Selden (1999), Coondoo and Dinda (2002), Friedl and Getzner (2003), Barassi and Spagnolo (2012), and others) leading to inconclusive results. The second research area deals with the link between energy consumption and income and aims at establishing the direction of causality between these two variables (see Yu and Jin (1992), Shiu and Lam (1994) and Glasure and Lee (1998) as illustrative examples of the empirical results provided in the literature).[5]

An important limitation of the literature linking emissions to income is that relevant variables may be omitted thereby hiding some important features of the intimate relationship between environmental quality and economic growth. The idea then emerges to consider energy consumption as an additional variable in the analysis of the EKC giving rise to a growing and very active literature dealing with the new emissions-energy-growth nexus.

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[5] Ozturk (2010) provides an excellent – and highly exhaustive – survey to this literature. See also the Table 1 in Al-Mulali et al. (2015) which report the main features of the many numerous studies dealing with this issue.

A central aspect of characterizing China's and India's energy-income-emissions nexus is the direction of causality between the components. Auffhammer and Carson (2008) suggest that the anticipated path of China's CO_2 emissions has dramatically increased over the last five years. The magnitude of the projected increase in Chinese emissions out to 2010 is several times larger than reductions embodied in the Kyoto Protocol. But what can be the causes of such a path for carbon emissions? To answer this question, Ang (2009) attempts to explore the determinants of CO_2 emissions in China using aggregate data for more than half a century applying an analytical framework that combines the environmental literature with modern endogenous growth theories. The results indicate that carbon emissions in China are negatively related to research intensity, technology transfer and the absorptive capacity of the economy to assimilate foreign technology. The findings also indicate that more energy use, higher income and greater trade openness tend to cause more CO_2 emissions.

Chang (2010) uses multivariate cointegration Granger causality tests to investigate the relationships between carbon dioxide emissions, energy consumption and economic growth in China. The discussion of his findings explains how the exclusive pursuit of economic growth might increase energy consumption and CO_2 emissions.

Liu et al. (2007) investigate the existence of an EKC for Shenzhen using environmental monitoring data dating back to 1980s. Recall that Shenzhen is the first special economic zone established in China in 1980. Interestingly, the authors note that: "[…] production-induced pollutants support EKC while consumption-induced pollutants do not support it." (p. 559) However, the fact that an EKC should exist in very economically specific region – at the regional level – remains an open question.

A few studies attempts to analyze the empirical validity of the EKC over a longer period (see Markandya et al. (2006), Lindmark (2002) or Fosten et al. (2012)). While the basis for statistical analysis in these papers is better as more observations are in hand, this kind of analysis is not likely to be possible for developing economies where the data does not often exist in a far past. In this regard, our work makes use of the largest data set available for China and India.

2.2 *The contribution of additional control variables*

A possible explanation for mixed results from EKC tests is that, beyond energy consumption, other relevant variables are omitted from the analysis. Carson (2010) emphasizes this point and mentions it as a major source of misspecification in current econometric studies looking at the EKC.[6] As a consequence, researchers have focused not only on energy, emissions and income, but they have extended their analyses to include other variables such as the level of trade openness of a country.

The literature concerning the relationship between CO_2 emissions and foreign trade considers the idea that developed economies have a higher specialization in human or physical capital which is less emission-intensive than those activities pursued by developing countries. Trade may therefore result in increased pollution in developing countries due to the increased production of emission-

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[6] Another source of misspecification highlighted in Carson (2010) is the functional form bias. This is also a central point in Musolesi and Mazzanti (2014) and we refer the interested reader to this article for references on this particular issue. In using the ARDL approach, we adopt a richer specification than in most of existing studies which make use of co-integration analysis.

intensive goods for export to developed nations. The study performed by Grossman and Krueger (1991) is pioneering in this regard, while additional research along this line of inquiry has also been addressed by Wyckoff and Roop (1994), Suri and Chapman (1998), and others. The results of these studies, however, are inconclusive in terms of the relationship between trade and environmental quality.

In a more recent study, Halicioglu (2009) documents that for the Turkish economy, income was the most crucial determinant of carbon emissions, followed by energy consumption and trade. Applying the ARDL approach of cointegration in a log linear quadratic relationship between per capita CO_2 emissions, per capita energy use, per capita real income, the square of per capita real income and the openness ratio, the author finds that there is both short and long-run bidirectional causality between carbon emissions and income in Turkey.

Soytas et al. (2007) investigate energy consumption, output and carbon emissions for the U.S. using the augmented vector autoregression (VAR) approach of Toda and Yamamoto (1995) (TY) after incorporating gross fixed capital formation and labor force into the model. They found no causal relationship between income and carbon emissions, or between energy use and income. However, the study found unidirectional Granger causality running from energy consumption to carbon emissions.

Using the same approach, Soytas and Sari (2009) obtain similar evidence of a link between income and carbon emissions in Turkey as well, but the unidirectional Granger causality ran from carbon emissions to energy consumption in the long-run. This implies that the U.S. and Turkey can reduce their carbon emissions without sacrificing economic growth. Sari and Soytas (2009) investigate the relationship between carbon emissions, income, energy and total employment in five OPEC countries by employing the autoregressive distributed lag (ARDL) model of cointegration. Cointegration among these variables has been established only for Saudi Arabia. The study established that none of countries studied, namely Algeria, Indonesia, Nigeria, Saudi Arabia and Venezuela, need to sacrifice economic growth in order to reduce carbon emissions.

Closest to our paper, Zhang and Cheng (2009), using the TY scheme, investigate the existence and direction of Granger causality between economic growth, energy consumption, and carbon emissions in China over the period 1960–2007. The authors control for capital and urban population and obtain results that suggest a unidirectional Granger causality running from GDP to energy consumption, and a unidirectional Granger causality running from energy consumption to carbon emissions in the long run. Evidence shows that neither carbon emissions nor energy consumption leads economic growth. Therefore, the government of China can purse conservative energy policy and carbon emissions reduction policy in the long run without impeding economic growth. Jalil and Mahmud (2009) have similarly found that carbon emissions are primarily determined by income and energy consumption, but trade had no significant impact on emissions. Also, the authors do not consider investment as a potential control variable in the regression analysis. At a more detailed level, however, Anderson et al. (2010) found that exports from China played an important role in generating emissions within the transport sector, which was greater than emissions attributable to imports. Incorporating endogenously determined structural breaks, Jayanthakumaran et al. (2012) found that CO_2 emissions were influenced by per capita income, structural changes and energy consumption.

Recent multivariate studies specific to India have found somewhat differing results. Ghosh (2010), using an autoregressive distributed lag (ARDL) bounds testing approach and Johansen-Juselius maximum likelihood procedure, found that carbon emissions and economic growth have short-run bidirectional causality, but none in the long-run. Importantly, while the author does control for the role of population growth, he does not control for trade openness. Jayanthakumaran et al. (2012) found that CO_2 emissions were influenced by per capita income and energy consumption, but not by structural changes. The same study found that, unlike China, trade openness had no significant long-run impact on carbon emissions.

Yuan et al. (2007) applies the cointegration theory to examine the causal relationship between electricity consumption and real GDP (Gross Domestic Product) for China during 1978–2004. Our estimation results indicate that real GDP and electricity consumption for China are cointegrated and there is only unidirectional Granger causality running from electricity consumption to real GDP but not the vice versa. Using a neo-classical aggregate production model, Yuan et al. (2008) investigates for the existence and direction of causality between output growth and energy use in China at both aggregated and disaggregated levels. Using the VEC specification, the short-run dynamics of the interested variables are examined, indicating that there exists Granger causality running from electricity and oil consumption to GDP, but does not exist Granger causality running from coal and total energy consumption to GDP. On the other hand, short-run Granger causality exists from GDP to total energy, coal and oil consumption, but does not exist from GDP to electricity consumption.

Sari and Soytas (2006) investigates the temporal relationship between the growth rates of energy consumption and GDP in China in a multivariate framework and evidence suggests that China may consider reducing the growth of energy consumption without significantly hampering economic growth. Wolde-Rufael (2004) investigates the causal relationship between various kinds of industrial energy consumption and GDP in Shanghai for the period 1952–1999 and evidence from disaggregated energy series seems to suggest that there was a uni-directional Granger causality running from coal, coke, electricity and total energy consumption to real GDP but no Granger causality running in any direction between oil consumption and real GDP. Agras and Chapman (1999) find no significant evidence for the existence of an EKC within the range of current incomes for energy in the presence of price and trade variables. Using the input–output analysis (IOA), Ang (2009) findings also indicate that more energy use, higher income and greater trade openness tend to cause more CO_2 emissions.

3. Econometric approach

3.1 *Data*

Our empirical analysis relies on annual data which is the best frequency for which such data is available. More specifically, we consider the annual data for China and India on CO_2 emissions (CO2) in metric tons per capita, energy consumption (ENG) in kg of oil equivalent per capita, real GDP (GDP) in constant 2000 US$ per capita, openness ratio (OPN) which is used as a proxy for foreign trade defined as the sum of exports and imports divided by the value of GDP in US$, and gross fixed capital formation (INV) in constant 2000 US$ which is used as a proxy for investment. All time series were collected from World Bank's well-known publication World Development Indicators (WDI-2013).

Although the output and CO_2 emissions series starts in 1960, the energy use series only begins in 1971 in the WDI. We thus choose the year 1971 as the starting year for our empirical work. The analysis was performed on the 1971-2009 period which is the largest sample period for such studies so far.

Table1. Descriptive statistics

	China					**India**				
	LCO_2	LENG	LGDP	LINV	LOPEN	$LC0_2$	LENG	LGDP	LINV	LOPN
Mean	0.792	6.651	6.084	25.760	3.291	-0.288	5.895	5.785	24.877	2.909
Std. Dev.	0.466	0.338	0.896	1.150	0.692	0.433	0.205	0.382	0.773	0.506
Skewness	0.281	0.674	0.173	0.173	-0.638	-0.195	0.284	0.562	0.397	0.430
Kurtosis	2.314	2.843	1.737	1.776	2.477	1.728	1.914	2.163	2.095	2.410

Notes: *LC02* is the log of carbon emissions, *LENG* is the log of energy consumption, *LGDP* is the log of real GDP per capita, *LOPN* is the log of the trade openness ratio as proxy for foreign trade, and *LINV* is the log of real gross fixed capital formation as a proxy for investment. Source: World Bank Indicators.

All the series were converted into logarithmic form. Descriptive statistics on CO_2 emissions, energy utilization, real GDP, trade, and real investment for China and India are presented in Table 1. Overall, most of the series are almost normally distributed.

3.2 *Methodology*

The EKC is increasingly called into question on the ground of weak econometric methods used to test its presence. Dinda (2004) and Huang et al. (2008) discuss this issue for the study of the environmental Kuznets curve and the investigation of the relationship between energy consumption and economic growth, respectively. Researchers have often made use of cointegration analysis keeping in mind that some series may be cointegrated thereby leading to spurious regressions results if standard methods were adopted.

To deal with the aforementioned issue, we use the ARDL modeling approach which was developed in Pesaran and Shin (1999) and later extended by Pesaran et al. (2001). This approach proposes to test for the existence of a relationship between the variables in levels in the system. It has a number of advantages compared to other cointegration techniques such as those developed in Engle and Granger (1987), Johansen (1988), Johansen and Juselius (1990) and Johansen (1996). First, it requires a smaller sample size. Second, it does not require variables to be integrated of the same order. It can be used regardless of whether the variables are purely *I(0)*, purely *I(1)*, or mutually cointegrated. As has been shown above, our data include a mix of *I(0)* and *I(1)* variables thereby strongly arguing for the use of the ARDL approach. Third, even though some of the model regressors are endogenous, the ARDL methodology provides unbiased long-run estimates and valid *t* statistics. And last, but not least, the ARDL modeling permits to estimate the short-run and long-run effects of one variable on the other simultaneously. The procedure relies on the well-known *F*-statistic to test the significance of the lagged levels of the variables in the representation of the ARDL model.

Our base model is as follows:

$$\Delta LC02_t = c_{1c} + \pi_{1c} LCO2_{t-1} + \pi_{2c} LENG_{t-1} + \pi_{3c} LGDP_{t-1} + \pi_{4c} LINV_{t-1} + \pi_{5c} LOPN_{t-1} + \\ \sum_{i=1}^{p} \theta_{ic} \Delta LC02_{t-i} + \sum_{i=1}^{q} \phi_{ic} \Delta LENG_{t-i} + \sum_{i=1}^{m} \gamma_{ic} \Delta LGDP_{t-i} + \sum_{i=1}^{n} \varphi_{ic} \Delta LINV_{t-i} + \sum_{i=1}^{r} \Psi_{ic} \Delta LOPN_{t-i} + u_{tc} \tag{1}$$

$$\Delta LENG_t = c_{1e} + \pi_{1e} LCO2_{t-1} + \pi_{2e} LENG_{t-1} + \pi_{3e} LGDP_{t-1} + \pi_{4e} LINV_{t-1} + \pi_{5e} LOPN_{t-1} + \\ \sum_{i=1}^{p} \theta_{ie} \Delta LC02_{t-i} + \sum_{i=1}^{q} \phi_{ie} \Delta LENG_{t-i} + \sum_{i=1}^{m} \gamma_{ie} \Delta LGDP_{t-i} + \sum_{i=1}^{n} \varphi_{ie} \Delta LINV_{t-i} + \sum_{i=1}^{r} \Psi_{ie} \Delta LOPN_{t-i} + u_{te} \tag{2}$$

$$\Delta LGDP_t = c_{1g} + \pi_{1g} LCO2_{t-1} + \pi_{2g} LENG_{t-1} + \pi_{3g} LGDP_{t-1} + \pi_{4g} LINV_{t-1} + \pi_{5g} LOPN_{t-1} + \\ \sum_{i=1}^{p} \theta_{ig} \Delta LC02_{t-i} + \sum_{i=1}^{q} \phi_{ig} \Delta LENG_{t-i} + \sum_{i=1}^{m} \gamma_{ig} \Delta LGDP_{t-i} + \sum_{i=1}^{n} \varphi_{ig} \Delta LINV_{t-i} + \sum_{i=1}^{r} \Psi_{ig} \Delta LOPN_{t-i} + u_{tg} \tag{3}$$

$$\Delta LINV_t = c_{1v} + \pi_{1v} LCO2_{t-1} + \pi_{2v} LENG_{t-1} + \pi_{3v} LGDP_{t-1} + \pi_{4v} LINV_{t-1} + \pi_{5v} LOPN_{t-1} + \\ \sum_{i=1}^{p} \theta_{iv} \Delta LC02_{t-i} + \sum_{i=1}^{q} \phi_{iv} \Delta LENG_{t-i} + \sum_{i=1}^{m} \gamma_{iv} \Delta LGDP_{t-i} + \sum_{i=1}^{n} \varphi_{iv} \Delta LINV_{t-i} + \sum_{i=1}^{r} \Psi_{iv} \Delta LOPN_{t-i} + u_{tv} \tag{4}$$

$$\Delta LOPN_t = c_{1o} + \pi_{1o} LCO2_{t-1} + \pi_{2o} LENG_{t-1} + \pi_{3o} LGDP_{t-1} + \pi_{4o} LINV_{t-1} + \pi_{5o} LOPN_{t-1} + \\ \sum_{i=1}^{p} \theta_{io} \Delta LC02_{t-i} + \sum_{i=1}^{q} \phi_{io} \Delta LENG_{t-i} + \sum_{i=1}^{m} \gamma_{io} \Delta LGDP_{t-i} + \sum_{i=1}^{n} \varphi_{io} \Delta LINV_{t-i} + \sum_{i=1}^{r} \Psi_{io} \Delta LOPN_{t-i} + u_{to} \tag{5}$$

In a first step, a bound-testing procedure is implemented so as to check for the existence of cointegrating relationship between pairs of variables. In so doing, we explore whether any dependent variable is linked in the long run to an explanatory (forcing) variable. At this stage, the *F*-statistic is used to test for the significance of the estimated coefficients for lagged variables. The test is applied for all possible regression combinations, each of which takes one variable as the dependent variable and the remaining variables as independent variables (Eqs. (1)–(5)). If a particular regression yields a significant *F*-statistic, then the variables are said to have a long-run relationship (be cointegrated), the regressors being the long-run forcing variables for the dependent variable.

Importantly, the *F*-statistics have to be compared with the lower and upper critical values. The null hypothesis of no cointegration cannot be rejected if the test statistic for the variable falls below the lower critical value. On the other hand, the null hypothesis will be rejected if the statistic is greater than the upper level critical value. When the statistic lies between the lower and upper bounds the test result is inconclusive.

The ARDL bounds test approach is to estimate Eqs. (1)-(5) using the ordinary least squares (OLS) method. The *F*-test is used in a bounds test for the existence of the long-run relationship (Pesaran et al, 2001), and it tests for the joint significance of lagged level variables involved. For each equation, the null hypothesis of the non-existence of a long-run relationship is that all estimated slope parameters are not significantly different from zero. For instance, for Eq. (1), the null hypothesis is (H_0: $\forall\, i = 1, \ldots, 5\ \pi_{ic} = 0$) against the alternative hypothesis (H_1: $\exists i \in \{1, \ldots, 5\}\ \pi_{ic} \neq 0$). Similarly, we compute *F*-statistics when considering the other four variables in turn as the dependent variables.

In the second step, we determine the optimal lag length for each variable in each equation on the basis of the Schwarz-Bayesian Criterion (SBC) which is preferred to the Akaike Information Criterion (AIC) on the basis of the findings in Narayan (2004) and Pesaran and Shin (1998) who argue that the SBC-based ARDL model performs better than the AIC-based model.

Finally, the third step is dedicated to the investigation of short-run dynamics through the estimation of error-correction models. The estimated models are given in Eqs. (1)-(6) and follow from the results in the first step about the cointegration analysis for each variable. Note that to ensure convergence of the dynamics to the long-run equilibrium, the sign of the coefficient for the lagged error correction term (ECT) must be significantly negative.

A general error-correction model is then formulated as follows:

$$\Delta LC02_t = c_{1c} + \sum_{i=0}^{p} \theta_{ic} \Delta LC02_{t-i} + \sum_{i=0}^{q} \phi_{ic} \Delta LENG_{t-i} + \sum_{i=0}^{m} \gamma_{ic} \Delta LGDP_{t-i} +$$

$$\sum_{i=0}^{n} \varphi_{ic} \Delta LINV_{t-i} + \sum_{0=1}^{r} \Psi_{ic} \Delta LOPN_{t-i} + \lambda_c ECT_{t-1} + \xi_{tc} \qquad (6)$$

$$\Delta LENG_t = c_{1e} + \sum_{i=0}^{p} \theta_{ie} \Delta LC02_{t-i} + \sum_{i=0}^{q} \phi_{ie} \Delta LENG_{t-i} + \sum_{i=0}^{m} \gamma_{ie} \Delta LGDP_{t-i} +$$

$$\sum_{i=0}^{n} \varphi_{ie} \Delta LINV_{t-i} + \sum_{i=0}^{r} \Psi_{ie} \Delta LOPN_{t-i} + \lambda_e ECT_{t-1} + \xi_{te} \qquad (7)$$

$$\Delta LGDP_t = c_{1g} + \sum_{i=0}^{p} \theta_{ig} \Delta LC02_{t-i} + \sum_{i=0}^{q} \phi_{ig} \Delta LENG_{t-i} + \sum_{i=0}^{m} \gamma_{ig} \Delta LGDP_{t-i} +$$

$$\sum_{i=0}^{n} \varphi_{ig} \Delta LINV_{t-i} + \sum_{i=0}^{r} \Psi_{ig} \Delta LOPN_{t-i} + \lambda_g ECT_{t-1} + \xi_{tg} \qquad (8)$$

$$\Delta LINV_t = c_{1v} + \sum_{i=0}^{p} \theta_{iv} \Delta LC02_{t-i} + \sum_{i=0}^{q} \phi_{iv} \Delta LENG_{t-i} + \sum_{i=0}^{m} \gamma_{iv} \Delta LGDP_{t-i} +$$

$$\sum_{i=0}^{n} \varphi_{iv} \Delta LINV_{t-i} + \sum_{i=0}^{r} \Psi_{iv} \Delta LOPN_{t-i} + \lambda_v ECT_{t-1} + \xi_{tv} \qquad (9)$$

$$\Delta LOPN_t = c_{1o} + \sum_{i=0}^{p} \theta_{io} \Delta LC02_{t-i} + \sum_{i=0}^{q} \phi_{io} \Delta LENG_{t-i} + \sum_{i=0}^{m} \gamma_{io} \Delta LGDP_{t-i}$$

$$+ \sum_{i=0}^{n} \varphi_{io} \Delta LINV_{t-i} + \sum_{i=0}^{r} \Psi_{io} \Delta LOPN_{t-i} + \lambda_o ECT_{t-1} + \xi_{to} \qquad (10)$$

where λ_j $(j=c,e,g,v,o)$ is the speed of adjustment parameter and ECT_{t-1} is the residual obtained from the estimation of Eqs. (1)-(5). In order to ensure that the correct statistical methods are applied to the model, diagnostic and stability tests are conducted. The diagnostic tests include testing for serial correlation, function form, normality and heteroscedasticity (Pesaran and Pesaran, 1997). In addition, the stability tests of Brown et al. (1975), which are also known as the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests based on the recursive regression residuals, were employed to that end.

4. Empirical findings

The *F*-statistics to gauge the presence of cointegration in Eqs. (1)-(5) are reported in Table 2 for both China and India. Because our sample size is moderately large and does not conform to conditions for the use of asymptotic values, we compute new relevant critical values for the sample size and the number of explanatory variables that are of interest in our empirical work. The critical values for the F-test are computed using simulations (20000 replications) and are reported in the Appendix.

Table 2. Bounds-testing Procedure for China and India

Cointegration hypothesis	F-statistics	
	China	India
$F(LCO2_t\|LENG_t, LGDP_t, LINV_{t,} LOPN_{t,})$	5.236^{*}[5]	6.189^{*}[4]
$F(LENG_t\|LC02_t, LGDP_t, LINV_{t,} LOPN_{t,})$	4.247^{**}[3]	7.408^{*}[5]
$F(LGDP_t\|LC02_{t,} LENG_t, LINV_{t,} LOPN_{t,})$	5.482^{*}[4]	4.608^{**}[5]
$F(LOPN_t\| LC02_t ,LENG_t, LGDP_t, LINV_t)$	4.682^{*}[3]	2.448[5]
$F(LINV_t \| LC02_t , LENG_t, LGDP_t, LOPN_t)$	15.097^{*}[5]	2.502[5]

Notes: The critical value bounds are computed by stochastic simulations using 20000 replications. * and ** indicate a rejection of the null hypothesis of no cointegration at the 5% and 10% level of significance (simulated values are reported in the appendix), respectively. The lag order is shown in brackets.

Results in Table 2 provide evidence of cointegrating relationships for all variables taken as the dependent variable in the case of China, as the Wald *F*-statistics all are above the simulated upper bound critical value. For India, the results show that there is evidence of cointegration when the CO_2 emissions, energy utilization and real GDP are taken as dependent variables in the model. However, when trade openness and real investment are taken as the dependent variable, the results of the bounds testing approach show that there is no cointegration relationship among the variables, as the Wald *F*-statistics are below the simulated lower bound critical value.

Therefore, the CO_2 emissions, energy utilization, real GDP, trade, and real investment equations were estimated with error-correction terms for China, and the CO_2 emissions, energy utilization and real GDP equations were estimated for India.

4.1 Long-run estimates

We now consider the ARDL procedure to estimate the coefficients of the long-run relationships. Results are reported in Table 3. The significant *F*-test indicates the presence of co-integration and suggests a model in which the forcing variables are the independent variables. In ARDL models, each independent variable has a lag. To determine the appropriate lag length for bounds testing procedure, given our sample size, the SBC is preferred to the AIC for selection of the lag. The long-run coefficients of the selected ARDL models based on the SBC are presented in Table 3 for both China and India.

We first discuss the empirical findings for China. According to the SBC model specification, the coefficient of energy utilization is highly significant and positive when carbon emissions is the dependent variable, and the coefficient of carbon emissions also is positive and significant, while to a lesser extent, when energy use is the dependent variable. This relationship between pollution and energy consumption is found in most of the existing literature as, for instance in Soytas et al. (2007), Soytas and Sari (2009), Jalil and Mahmud (2009) or Zhang and Cheng (2009). It can also be noted that with income as the dependent variable, all the coefficients are significant. Then, specific to our study, the coefficients of energy use and real income are significant when openness is the dependent variable. Nevertheless, with respects to long-run estimates, investment and openness seem to play a role in shaping the relationship between carbon emissions, energy consumption and income in China.

Table 3. Estimated Long-run Coefficients for China and India

Model selection	Dependent variable	INPT	$LCO2_t$	$LENG_t$	$LGDP_t$	$LINV_t$	$LOPN_t$
ARDL(1,2,1,0,1)	$LC02_{t\,CH}$	-2.900 [2.750]	---	0.537^{***} [0.151]	0.301 [0.205]	-0.079 [0.154]	0.075 [0.054]
ARDL(1,1,0,0,0)	$LENG_{tCH}$	3.957 [10.472]	1.654^{*} [0.853]	---	-0.366 [0.784]	0.189 [0.578]	-0.358 [0.335]
ARDL(1,0,0,0,0)	$LGDP_{t\,CH}$	-6.654^{**} [2.599]	0.798^{**} [0.326]	-0.749^{**} [0.315]	---	0.654^{***} [0.050]	0.107^{*} [0.059]
ARDL(2,0,0,1,0)	$LINV_{t\,CH}$	13.720^{***} [2.076]	-0.645^{*} [0.335]	0.655^{**} [0.310]	1.354^{***} [0.065]	---	-0.022 [0.059]
ARDL(5,5,5,4,4)	$LOPN_{t\,CH}$	-5.264 [14.910]	4.087^{**} [1.619]	-4.522^{*} [1.999]	-2.775 [2.079]	2.009 [1.436]	---
ARDL(2,3,1,0,2)	$LC02_{t\,IN}$	-21.351^{***} [2.247]	---	3.236^{***} [0.489]	-1.862^{***} [0.430]	0.513^{***} [.174]	0.010 [0.125]
ARDL(5,5,2,5,5)	$LENG_{t\,IN}$	-0.425 [8.437]	0.018 [0.298]	---	0.375 [0.267]	0.182 [0.403]	-0.131 [0.167]
ARDL(5,4,2,0,4)	$LGDP_{t\,IN}$	-12.266^{***} [1.907]	-0.302^{**} [0.136]	1.087^{**} [0.479]	---	0.461^{***} [0.140]	0.051 [0.058]

Notes: Standard errors are shown in brackets. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

As for India, all the coefficients are significant except openness when emissions are the dependent variable. In particular, the investment variable is significant at the 1% level, thereby emphasizing the important role of this covariate as a control variable. In terms of the energy equation, none coefficient is significant at any threshold, which does not exclude the existence of potential causal relationships as found in Ghosh (2010) in the case of India. Finally, for the income as the dependent variable, all the coefficients are highly significant except openness.

Overall, our results point to a weak role of foreign trade for both China and India as an explanatory variable. This lack of explanatory power for trade openness is in line with the findings in Halicioglu (2009) for the case of Turkey. Along with the fact that openness is only partly – and weakly – explained by energy use and emissions level for China and not explained by any variable considered in our study, we can conclude that foreign trade plays a minor role in the energy-pollution-growth nexus. This is an important result in light of the large share of exports for both countries.

As for the investment level, the results are noticeably different for each country. Indeed, while the capital variable is not explained by any covariate in the case of India, emissions, energy consumption and GDP explain investment for China. This highlights a specific feature of China, partly raised in Zhang and Cheng (2009), that capital accumulation is caused by energy use while energy use is quite inoperative for India. Possible explanation for this finding is the size of the financial sector in China, which is far larger than in India, and facilitates corporate financing.

More generally, we emphasize a large number of long-run relationships between selected variables. Residuals from models defined in Eqs. (1) to (5) will be used as the error-correction-term (ECT) to estimate the short-term specifications defined in Eqs. (6) to (10).

4.2 Short-run estimates

Results from the error-correction models are reported in Table 4 with the panel A being dedicated to China and the panel B being devoted to India.

Table 4. Error correction representation for the selected ARDL models

Panel A: China

Variables in equation	Dependent variable (CO_2)	Dependent variable (ENG)	Dependent variable (GDP)	Dependent Variable (INV)	Dependent Variable (OPN)
$\Delta LCO2_t$	---	0.679*** [0.070]	0.297** [0.113]	-0.155 [0.287]	0.689 [0.833]
$\Delta LCO2_{(t-1)}$	---	---	---	---	-3.342*** [1.025]
$\Delta LCO2_{(t-2)}$	---	---	---	---	-5.341*** [1.293]
$\Delta LCO2_{(t-3)}$	---	---	---	---	-4.484*** [1.417]
$\Delta LCO2_{(t-4)}$	---	---	---	---	-3.552*** [1.025]
$\Delta LENG_t$	0.853*** [0.113]	---	-0.279** [0.109]	0.546** [0.264]	1.702 [1.073]
$\Delta LENG_{(t-1)}$	0.446*** [0.122]	---	---	---	5.200*** [1.332]
$\Delta LENG_{(t-2)}$	---	---	---	---	4.859** [1.583]
$\Delta LENG_{(t-3)}$	---	---	---	---	6.509*** [2.025]
$\Delta LENG_{(t-4)}$	---	---	---	---	3.126** [1.337]
$\Delta LGDP$	0.482*** [0.161]	-0.037 [0.081]	---	1.129*** [0.189]	2.942*** [0.812]
$\Delta LGDP_{(t-1)}$	---	---	---	---	1.740* [0.954]
$\Delta LGDP_{(t-2)}$	---	---	---	---	2.499** [1.049]
$\Delta LGDP_{(t-3)}$	---	---	---	---	3.566*** [0.901]
$\Delta LINV$	-0.031 [0.064]	0.019 [0.060]	0.243*** [0.050]	---	-0.620 [0.406]
$\Delta LINV_{(t-1)}$	---	---	---	0.407*** [0.126]	-0.828* [0.423]
$\Delta LINV_{(t-2)}$	---	---	---	---	-1.119** [0.398]
$\Delta LINV_{(t-3)}$	---	---	---	---	-1.564*** [0.364]
$\Delta LOPEN$	-0.025 [0.033]	-0.036* [0.018]	0.040* [0.021]	-0.019 [0.050]	---
$\Delta LOPEN_{(t-1)}$	---	---	---	---	0.490** [0.199]
$\Delta LOPEN_{(t-2)}$	---	---	---	---	0.113 [0.227]
$\Delta LOPEN_{(t-3)}$	---	---	---	---	0.129 [0.243]
$\Delta LOPEN_{(t-4)}$	---	---	---	---	-0.530** [0.179]
ECM_{t-1}	-0.399*** [0.114]	-0.101 [0.106]	-0.372*** [0.063]	-0.834*** [0.137]	-0.600** [0.261]
CUSUM	[Stable]	[Stable]	[Stable]	[Stable]	[Stable]
CUSUMSQ	[Stable]	[Stable]	[Stable]	[Stable]	[Stable]

Panel B: India

Variables in equation	Dependent variable (CO_2)	Dependent Variable (ENG)	Dependent Variable (GDP)
$\Delta LCO2$	---	0.009 [0.202]	0.447*** [.123]
$\Delta LCO2_{(t-1)}$	-0.575*** [0.155]	-0.344 [0.221]	.526*** [0.093]
$\Delta LCO2_{(t-2)}$	---	0.232 [0.196]	---
$\Delta LCO2_{(t-3)}$	---	0.599** [0.217]	---
$\Delta LCO2_{(t-4)}$	---	0.497*** [0.131]	---
$\Delta LGDP$	0.233 [0.261]	0.159 [0.270]	---
$\Delta LGDP_{(t-1)}$	0.609*** [0.189]	0.413 [0.247]	-0.082 [0.175]
$\Delta LGDP_{(t-2)}$	0.334* [0.177]	---	-0.344** [0.145]
$\Delta LGDP_{(t-3)}$	---	---	-0.153 [0.110]
$\Delta LGDP_{(t-4)}$	---	---	-0.284** [0.101]
$\Delta LENG_t$	-0.079 [0.311]	---	-0.063 [0.145]
$\Delta LENG_{(t-1)}$	---	0.858 [0.677]	-0.840*** [0.244]
$\Delta LENG_{(t-2)}$	---	0.281 [0.538]	-0.521** [0.233]
$\Delta LENG_{(t-3)}$	---	0.299 [0.507]	0.439* [0.236]
$\Delta LENG_{(t-4)}$	---	-0.999** [0.345]	---
$\Delta LINV_t$	0.212** [0.098]	0.120 [0.102]	0.210*** [0.053]
$\Delta LINV_{(t-1)}$	---	-0.263*** [0.083]	---
$\Delta LINV_{(t-2)}$	---	-0.218** [0.093]	---
$\Delta LINV_{(t-3)}$	---	-0.251*** [0.075]	---
$\Delta LINV_{(t-4)}$	---	-0.117* [0.060]	---
$\Delta LOPN_t$	0.037 [0.063]	-0.076 [0.054]	-0.113*** [0.034]
$\Delta LOPN_{(t-1)}$	-0.163** [0.068]	0.058 [0.068]	0.123*** [0.040]
$\Delta LOPN_{(t-2)}$	---	-0.003 [0.079]	-0.070* [0.034]
$\Delta LOPN_{(t-3)}$	---	-0.009 [0.068]	-0.088** [0.039]
$\Delta LOPN_{(t-4)}$	---	0.187** [0.073]	---
ECM_{t-1}	-0.414*** [0.117]	-0.666 [0.755]	-0.455* [0.220]
CUSUM	[Stable]	[Stable]	[Stable]
CUSUMSQ	[Stable]	[Stable]	[Stable]

Notes: Standard errors are shown in the square brackets under each coefficient. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The results of short-run models are reported based on the bounds testing procedure. For China, we observe that the variation in energy consumption and growth has a positive and highly significant impact on the change in carbon emissions. This dynamics is supported by the coefficient of the ECT, which is, as expected, negative and statistically significant. These results are in line with those in Zhang and Cheng (2009), among others. Also, CO_2 growth and the variation in trade openness impede energy consumption. Next, in the short-run, all coefficients are statistically significant when the economic growth is the dependent variable. Moreover, we show Granger causality from CO_2 emissions, energy use, investment and openness to the output in the long-run, as is shown from the coefficient of the ECT, which is negative and statistically significant. Then, the scenario for investment is impeded by energy consumption change and growth and the negative sign of the ECT confirms the expected convergence process in long-run dynamics of investment model for China. Finally, and most interestingly, the openness taken as the dependent variable leads to all variables being highly significant at all lags thereby pointing out to strong relationships between pollution, energy use, income, investment and trade openness in the short-run.

In the case of India, we find growth, trade openness and investment to have a significant impact on the current CO_2 variation and the dynamics is supported by the coefficient of the ECT. This is similar to Ghosh's (2010) results at least for growth and investment as openness is not present in his study. Only the short-run lagged coefficients are significant for investment in the energy equation but this is not validated through an insignificant parameter estimate for the ECT. This confirms the intuition from the estimation of long-run model where investment does not play a central role in India. Finally, as is the case for China, we obtain highly significant parameter estimates for most of selected variables in the growth equation, while with a mixed support from the ECT estimate, which only is marginally significant.

Overall, results confirm empirical findings from the previous section where investment is a key variable in China but not in India. Moreover, while openness only plays a minor role in the long-run in China but a fairly noteworthy function in the short-run, the picture is radically different in India. Indeed, Indian trade openness does contribute neither in the long-run nor in the short-run to the dynamics of our set of variables.

4.3 Robustness analysis

The ARDL technique requires a series of diagnostic and stability tests to gauge the robustness of the results. We check for serial correlation and functional form by utilizing the Lagrange Multiplier test of residual serial correlation and Ramsey's RESET test. The normality hypothesis is assessed through the examination of both the skewness and the kurtosis of residuals. Finally, for constant variance, we look at the regression of squared residuals on squared fitted values. The diagnostic tests reveal no important evidence of misspecification and autocorrelation at the 5% level. The adjusted R-squared values are in the vicinity of 50 percent, signifying a good fit of the models. Finally, we test for structural stability by employing the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of residuals (CUSUMSQ). No serious problems have been identified. The plots[7] of the CUSUM and CUSUMSQ statistics are well within the critical bounds, implying that all coefficients in the ECM model are stable over the sample period

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[7] The figures are not presented but are available upon request.

1971-2009. The results of the diagnostic tests suggest that the underlying desirable assumptions are fulfilled.

Table 5. Diagnostic tests

Panel A: China

	Dependent variable (CO_2)	Dependent variable (ENG)	Dependent variable (GDP)	Dependent variable (INV)	Dependent variable (OPN)
Serial correlation	F(1,23)=0.350 [0.560]	F(1,28)=2.925 [0.098]	F(1,28)=0.017 [0.899]	F(1,26)=0.259 [.615]	F(1,5)=39.946 [0.001]
Functional form	F(1,23)=2.025 [0.168]	F(1,28)=6.106 [0.020]	F(1,28)=.258 [0.616]	F(1,26)=2.318 [0.140]	F(1,5)=0.174 [0.694]
Normality	$\chi^2(2)=1.107$ [0.575]	$\chi^2(2)=1.299$ [0.522]	$\chi^2(2)=1.435$ [0.488]	$\chi^2(2)=4.180$ [0.124]	$\chi^2(2)=0.277$ [0.871]
Heteroscedasticity	F(1,32)=0.426 [0.518]	F(1,34)=0.019 [0.891]	F(1,33)=0.656 [0.424]	F(1,33)=0.147 [0.704]	F(1,32)=0.358 [0.554]

Panel B: India

	Dependent variable (CO_2)	Dependent variable (ENG)	Dependent variable (GDP)
Serial correlation	F(1,21)=0.212 [0.650]	F(1,6)=1.596 [0.253]	F(1,13)=0.142 [0.712]
Functional form	F(1,21)=3.146 [0.091]	F(1,6)=2.759 [0.148]	F(1,13)=5.677 [0.033]
Normality	$\chi^2(2)=0.813$ [0.666]	$\chi^2(2)=2.856$ [0.240]	$\chi^2(2)=.706$ [0.702]
Heteroscedasticity	F(1,33)=3.348 [0.076]	F(1,32)=0.220 [0.642]	F(1,32)=0.007 [0.934]

Notes: *P*-values are shown in the square brackets under each coefficient

4.4 Potential extensions

As potential extensions to the present work, the contribution of Rothman (1998) who makes use of consumption-based measures – such as municipal wastes – of environmental impact may deliver a different picture of the EKC in the context of developing economies. Other measures of environmental, such as the Ecological Footprint (EF) used in Caviglia-Harris et al. (2009), may also be used in this regard. Another possible extension is to include additional control variables such as energy prices. Agras and Chapman (1999) test the energy-income and CO2-income relationships using EKC framework. They find that the income is no longer the most relevant indicator of environmental quality when prices are included as additional control variables.

5. Conclusion

In this paper, we conduct an econometric analysis of the relationship between carbon emissions, energy consumption and income. Our results, over the 1971-2009 period, provide evidence that investment plays a major role in shaping the relationship between carbon emissions, energy consumption and income in China, while this is not the case in India. Furthermore, trade openness is found to play a key function in the short-term in China but does not contribute to the emissions-energy-growth scenario in India.

This finding potentially comes from the difference in economic structure and policies in China and India. While China has, over the last three decades, made huge investments in manufacturing industries and gradually sought constant technological improvements to enhance energy efficiency and reduce carbon emissions, India still has a commodity-based economy and remains lagged behind with respect to technologies.

Our results also provide policy implications such as the effort to be made by India to make its energy use more effective with respect to capital accumulation. In this vein, Ghosh (2010) notes that “India must boost its energy-related research and development for the diffusion of cleaner technologies in the future (p. 3013)”. As for China, because energy use Granger-causes emissions while the relationship does not go the other way around, obvious recommendations for the Chinese government would be to encourage the use and development of cleaner energy sources. The recent positioning of China at the COP21 in Paris (December 2015) may be helpful in this respect. On this occasion, the Chinese government promised indeed to modernize its coal power plants by 2020 in order to cut their pollutant emissions by 60% or about 180 million tons of CO_2 emissions each year.

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Appendix: Asymptotic critical value for F-tests

Cointegration hypothesis	Asymptotic critical value	95% CV		90% CV	
		I(0)	I(1)	I(0)	I(1)
$F_{CH}(LCO2_t \mid LENG_t, LGDP_t, LOPN_t, LINV_t)$	F(5,2)	3.300	4.678	2.748	3.905
$F_{CH}(LENG_t \mid LC02_t, LGDP_t, LOPN_t, LINV_t)$	F(5,14)	3.302	4.665	2.719	3.939
$F_{CH}(LGDP_t \mid LC02_{t,} LENG_t, LOPN_t, LINV_t)$	F(5,8)	3.316	4.700	2.742	3.921
$F_{CH}(LOPN_t \mid LC02_t, LENG_t, LGDP_t, LINV_t)$	F(5,14)	3.302	4.665	2.719	3.939
$F_{CH}(LINV_t \mid LC02_t, LENG_t, LGDP_t, LOPN_t)$	F(5,2)	3.300	4.678	2.748	3.905
$F_{IN}(LCO2_t \mid LENG_t, LGDP_t, LOPN_t, LINV_t)$	F(5,8)	3.316	4.700	2.742	3.921
$F_{IN}(LENG_t \mid LC02_t, LGDP_t, LOPN_t, LINV_t)$	F(5,2)	3.300	4.678	2.748	3.905
$F_{IN}(LGDP_t \mid LC02_{t,} LENG_t, LOPN_t, LINV_t)$	F(5,2)	3.300	4.678	2.748	3.905
$F_{IN}(LOPN_t \mid LC02_t, LENG_t, LGDP_t, LINV_t)$	F(5,2)	3.300	4.678	2.748	3.905
$F_{IN}(LINV_t \mid LC02_t, LENG_t, LGDP_t, LOPN_t)$	F(5,2)	3.300	4.678	2.748	3.905