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On the economic growth and environmental quality nexus in India

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ABSTRACT

This study extends prior research and takes a robust account of the effects of economic growth on environmental quality in India, using several single-equation and system estimators and considering multiple structural breaks over '*long*' as well as '*short*' time periods. The long-run model is estimated on annual data for the period 1951–52 to 2015–2016. The results provide robust support for the positive and significant effects of gross domestic product and financial development and for the negative effects of trade openness and domestic investment on carbon dioxide emissions. The presence of structural breaks challenges the validity of smooth and continuous relationship between income and emissions postulated in previous research. Policy intervention, in terms of the imposition of Pigouvian tax, allocation of carbon quotas and promotion of carbon 'cap-and-tax' and/or 'cap-and-trade' systems, is needed to correct market failure, to cover the external cost of pollution and to curtail the emission of carbon. It is worth subsidizing alternative sources of energy, adopting carbon-efficient technologies and switching to carbon-neutral substitutes.

KEYWORDS

Economic growth; carbon dioxide emissions; pollution; environmental quality

JEL CLASSIFICATION

O44; Q51; Q52; Q53

I. Introduction

The global warming and ecological imbalance arising from the emissions of greenhouse gases has aroused enormous environmental, social and policy concerns, and has posed daunting challenges for environmentally sustainable development strategies. The negative externalities of economic growth and the socio-environmental costs of emissions of greenhouse gases (GHG), in terms of health hazards and damages to ecosystems, are shared globally through atmospheric diffusion, rather than exclusively locally at the point of origin (Herweg and Schmidt 2022; Shapiro 2021; World Bank 2018). The free rider behaviour of emitters, the tragedy of the commons and the public-good nature of GHG emissions, with their lack of localization or internalization of costs, all tend to impede the decline in emissions even at theoretically predicted higher levels of income. The Environmental Kuznets Curve (EKC) first suggested by Panayotou (1993) and almost contemporaneously articulated by Grossman and Krueger (1991, 1995) postulates an inverted U-shaped relationship between a measure of pollution and income. The economic development is accompanied by the degradation of environmental conditions in the initial stages and, after a certain point, by the reduction in pollution and an improvement in environmental quality.

The theoretically postulated quadratic polynomial of EKC seems empirically tenable for the developed countries that have achieved high levels of income and thus have progressively been able to afford cleaner or green technologies. Most developing countries have not yet reached those levels of income that are sufficiently high to generate the turning points in the emission – income trajectory, as predicted by the EKC theory. They find it hard to afford pollution abatement expenditures and thus to adopt emission-efficient technologies. Several factors, including reliance on obsolete technologies and lackadaisical motivation to mitigate emission, delay the turning point in the emission – income trajectory in the developing countries.

This study examines the effects of economic growth on environmental quality in India. The long-run model is estimated on annual data for the period 1951–52 to 2015–2016. The study contributes to the extant literature on several counts.

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First, all studies conducted to date have measured financial development – used as one of the control variables in the model – in terms of standard indicators, including (i) ratio of bank (private) credit to gross domestic product (GDP), (ii) ratio of stock market capitalization to GDP and (iii) ratio of monetary aggregates to GDP. These measures are beset with several inherent limitations (Singh 2008). This study draws on Goldsmith (1969, 1983) and measures financial development in terms of finance ratio. Second, prior research has focused on EKC-type smooth and continuous relationship between income and emissions. This study follows an alternative approach and tests for structural breaks over both '*long*' and '*short*' time periods. Third, the academic debates and economic controversies – which surface in almost every area of empirical research – could be partially ascribed to the use of different methodologies and test statistics across studies (Singh 2022). This study uses a battery of estimators to estimate the model and assess the robustness of results across methodologies.

The evidence drawn from multiple estimators provides robust support for the positive and significant effects of GDP and financial development and for the negative effects of trade openness and domestic investment on carbon dioxide emissions. Policy intervention, in terms of the imposition of Pigouvian tax, allocation of carbon emission permits and promotion of carbon 'cap-and-tax' and/or 'cap-and-trade' systems, is needed to correct market failure, to cover the external cost of pollution and to curtail the emission of carbon. It is worth subsidizing alternative sources of energy, adopting carbon-efficient technologies and switching to carbon-neutral substitutes. It is important to enhance openness to trade and to encourage domestic investment, especially the investment linked to cleaner production and green technologies, to develop a low or no carbon economy.

The remainder of the study is structured as follows. Section II undertakes descriptive analysis and presents stylized facts. Section III reviews the literature. Section IV specifies the model. Section V presents the empirical results. Section VI discusses the results and provides policy perspectives. Section VII concludes the study.

II. Descriptive analysis and stylized facts

Economic growth

India witnessed slow/low economic growth for a prolonged period from the 1950s through to the 1970s. The acceleration of growth in the initial stages of economic development in the 1950s – with low level of industrial development, underdeveloped infrastructure, meagre foreign exchange reserves and low rates of domestic saving and investment – required a 'big-push' (*a la* Rosenstein-Rodan 1943) in terms of the quantum of investment. The rate of gross domestic saving (GDS) was abysmally low, at 10.19% in the 1950s and 12.69% in the 1960s. Since domestic saving finances a significant proportion of domestic investment, the rate of domestic investment – rate of gross domestic capital formation (GDCF) – was also commensurately low, at 11.33% in the 1950s and 14.63% in the 1960s.

The green revolution of the mid–1960s transformed forests into farmlands. Such deforestation, coupled with large-scale use of toxic pesticides and fertilizers, led to the degradation of environmental quality. The economic growth averaged 3.59% in the 1950s, 3.96% in the 1960s, 2.94% in the 1970s and 5.58% in the 1980s. The cumulative effects of persistently slow/low economic growth, sluggish exports, fiscal deformities and market distortions culminated into the balance of payments crisis in the early 1990s. This led to a paradigm shift in policy regime and the emergence of a new economic order. The economic growth averaged 5.84% in the 1990s, 7.21% in the 2000s and 6.85% in the 2010s (2010–11 to 2017–18). The services sector bypassed the completion of industrialization, emerging as the dominant driver of economic growth after the onset of economic reforms. The supremacy of services sector – in terms of its share in GDP and contribution to economic growth – strengthened the resilience of the economy to the shocks of weather aberrations affecting agriculture. The rate of GDS rose from 17.34% in the 1970s to 29.34% in the 2010s and that of GDCF from 17.47% to 31.76% over the same period. The openness to trade, which remained restrictive until the 1980s, showed a significant surge following the onset of economic reforms (Table 1, Figure 1).

Table 1. Economic growth and macroeconomic parameters in India.

Period	Growth of real GDP (%)	Rate of GDS (%)	Rate of GDCF (%)	Exports as % of GDP	Imports as % of GDP	Trade openness as % of GDP
1950-51 to 1959-60	3.59@	10.19	11.33	5.10	6.81	11.90
1960-61 to 1969-70	3.96	12.69	14.63	3.26	5.15	8.41
1970-71 to 1979-80	2.94	17.34	17.47	4.24	5.37	9.61
1980-81 to 1989-90	5.58	18.59	20.37	4.55	7.67	12.23
1990-91 to 1999-00	5.84	22.96	24.32	7.73	10.49	18.22
2000-01 to 2009-10	7.21	30.64	31.21	11.95	17.18	29.13
2010-11 to 2017-18	6.85	29.34	31.76	14.55	22.04	36.59

(1) Growth of real GDP is measured in terms of the growth of GDP at factor cost at constant prices, base year 2004–05; (2) @ denotes growth of real GDP for the period 1951–52 to 1959–60; (3) Rates of GDS and GDCF each are measured as a percentage of GDP at current market prices; (3) Trade openness (TO) is measured in terms of exports (X) plus imports (M) as a percentage of GDP at market prices such that $TO = [(X + M)/GDP] \times 100$; all at current prices.

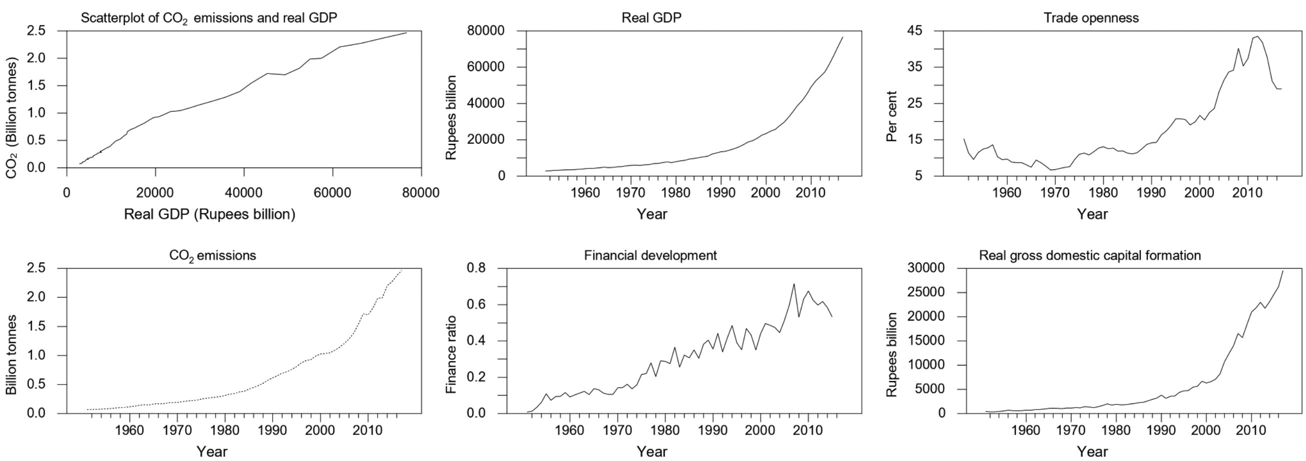

Figure 1. Scatterplot and time trajectories of the model variables.

Carbon emissions

Economic growth has been accompanied by an increase in pollution and a deterioration in environmental quality. Approximately 65% of the global GHG emissions are generated by the combustion of fossil fuels; of these, coal is responsible for 45%, oil 35% and natural gas 20% (Hsiang and Kopp 2018). India relies heavily on the combustion of fossil fuels (mainly coal and oil) for the generation of electric power, rather than low-carbon or carbon-neutral alternatives such as hydropower, natural gas, wind, solar and nuclear energy. Both coal and oil have high carbon content and they share the largest proportion (more than 80%) of primary energy consumption (Table 2). Heavy combustion of coal and oil has led to sharp increases in carbon dioxide (CO_2) emissions.

India is the third leading emitter of carbon in the world, after China and the U.S. The per capita emissions in India are about half the G20 average (UNEP 2019). The marginal propensity to emit carbon, as measured in terms of the gradient of the emission-GDP trajectory, was relatively low during the phase of slack economic growth in the 1950s through to the 1970s; became modest during the phase of modest growth in the 1980s; and then turned higher in the wake of rapid growth that took place following the onset of economic reforms from the early 1990s (Figure 1). The environmental conditions continue to worsen: the emission-GDP coordinates have yet to reach and pass the turning point in the trajectory (Figure 1).

The exponential trend function, $\ln y(t) = \alpha + \beta T + \varepsilon(t)$, is estimated to work out the annual average rate of growth, $r = \left\{\exp\left(\hat{\beta}\right) - 1\right\} \times 100$, and the quadratic trend function, $\ln y(t) = \alpha + \beta T + \delta T^2 + \varepsilon(t)$, is estimated to assess the acceleration, $\delta > 0$, or deceleration, $\delta < 0$, in CO_2 emissions, where T denotes the time trend and exp(.) the exponential of the parameter. Standard errors of the parameters are adjusted using the heteroscedasticity and autocorrelation consistent (HAC) estimator of Newey and West (1987).

Table 2. Compositional pattern of energy consumption in India (per cent).

	Coal and oil			Other					
Period	Coal	Oil	Total	Natural gas	Hydropower	Wind	Solar	Nuclear	Total
1965-69	63.84	26.56	90.40	0.51	9.04			0.05#	9.60
1970-79	56.56	30.69	87.25	1.11	11.14			0.50	12.75
1980-89	55.55	31.83	87.38	2.80	9.18			0.64	12.62
1990-99	55.31	30.94	86.25	6.07	6.91	0.04	0.00041@	0.72	13.74
2000-09	52.98	33.05	86.03	7.26	5.30	0.37	0.00151	1.03	13.96
2010-17	56.05	29.61	85.66	7.26	4.55	1.14	0.20597	1.19	14.35

(1) Sub-items may not exactly add up to totals because of rounding; (2) @ average for the period 1995–99; (3) Data for nuclear were available only from 1969 onwards. # share of nuclear was 0.25% for the year 1969.

The results suggest that carbon emissions have grown faster than GDP in both pre-reform (1951–1990) and full-sample (1951–2017) periods. The growth of CO_2 emissions became a shade lower than the growth of real GDP only in the post-reform period (1991–2017), not because of the decline in emissions *per se* but because of the relatively rapid growth of GDP. The growth of CO_2 emissions virtually remained unabated in both pre- and post-reform periods – it was 5.41% during 1951–1990 and 5.26% during 1991–2017 (Table 3). The annual average growth of CO_2 emissions at 5.54% has been higher than the growth of GDP at 4.97% during 1951–2017. The positive coefficient of the quadratic term, $\delta > 0$, suggests that the economy experienced acceleration in emissions, although the rate of such acceleration was numerically small, $\delta = 0.7966 \times 10^{-5}$, and statistically insignificant.

III. The literature review

The inverted U-shaped relationship between per capita income and environmental degradation (pollution) postulated in EKC theory is an adapted reformulation of the inverted U-shaped relationship between income inequality and per capita income pioneered by Kuznets (1955, 1966). The income disparities first rise and then decline during the process of economic development. This inverted U-shaped relationship between income inequality and per capita income came to be described as the Kuznets curve (hypothesis). Panayotou (1993) analogously coined the term Environmental Kuznets Curve (EKC) and, almost contemporaneously, Grossman and Krueger (1991, 1995) articulated the inverted U-shaped relationship between per capita income and environmental degradation (pollution). Environmental degradation first rises in the

Table 3. Estimates of the trend and quadratic trend functions.

	Trend function			Quadratic trend function		
	$\ln y(t) = \alpha + \beta T + \varepsilon(t)$		Rate of growth (per cent)	$\ln y(t) = \alpha + \beta T + \delta T^2 + \varepsilon(t)$		
Variable	α	β	r	α	β	δ
		Pre-reform period: 1951–1990				
$\ln CO_2$	−2.68***	0.05268***	5.41	−2.70***	0.05496***	-0.55581×10^{-4}
	(−78.64)	(39.69)		(−68.56)	(11.12)	(−0.44)
lnGDP	7.91***	0.03735***	3.81	7.96***	0.03032***	0.17154×10^{-3}
	(565.03)	(40.47)		(403.73)	(12.24)	(2.72)***
		Post-reform period: 1991–2017				
$\ln CO_2$	−2.54***	0.05123***	5.26	−1.14**	−0.00184	0.49135×10^{-3}
	(−35.02)	(39.08)		(−2.06)	(−0.09)	(2.51)**
lnGDP	6.71***	0.06749***	6.98	7.60***	0.03398**	0.31026×10^{-3}
	(132.84)	(77.73)		(21.32)	(2.48)	(2.44)***
		Full sample period: 1951–2017				
$\ln CO_2$	−2.70***	0.05394***	5.54	−2.69***	0.05340***	0.7966×10^{-5}
	(−107.83)	(97.08)		(−76.29)	(22.48)	(0.25)
lnGDP	7.71***	0.04848***	4.97	8.03***	0.02042***	0.41265×10^{-3}
	(103.78)	(22.78)		(233.46)	(10.31)	(16.13)***

(1) Figures in parentheses are t-values; (2) *** and ** indicate statistical significance at 1% and 5% levels, respectively; (3) The rate of growth, r, is computed as $r = \left\{\exp\left(\hat{\beta}\right) - 1\right\} \times 100$; (4) Some of the t-values are on the border line of critical region and thus strictly do not reject the null hypothesis at the indicated level of significance.

primitive stages of economic development with low levels of per capita income, due to several factors such as switching from agriculture to industry (manufacturing) as a corollary of the process of structural transformation, relying on obsolete technologies, using non-renewable sources of energy (such as combustion of fossil fuels) and lacking stringent environmental regulations and enforcements. The upward trend reverses beyond some level of per capita income so that environmental degradation starts declining. Such a decline in environmental degradation can be attributed to a multitude of factors: the switch from industry to services sector (with lower environmental impact than industry), the use of emission-efficient technologies, the adoption of stringent environmental regulations, and the switch to solar and renewable energy substitutes.

The empirical studies conducted in EKC domain provide a mixed and inconclusive evidence – some studies support (Brock and Taylor 2010; Fang, Huang, and Yang 2020; Frankel and Rose 2005; Grossman and Krueger 1995; Liddle and Messinis 2015; Liu, Liu, and Zhang 2023; Magazzino 2024; Selden and Song 1994; Yu et al. 2022) and some reject (Azomahou, Laisney, and Nguyen 2006; Erdoğan et al. 2020; Friedl and Getzner 2003; González-Álvarez and Montañés 2023; Harbaugh, Levinson, and Wilson 2002; Holtz-Eakin and Selden 1995; Shafik 1994) the validity of EKC. Some studies show a positive linear, rather than curvilinear, relationship between income and pollution (Azomahou, Laisney, and Nguyen 2006; Richmond and Kaufmann 2006; Shafik 1994).

The international trade serves as a conduit for the diffusion of atmospheric carbon across national boundaries (Copeland and Taylor 2004; Fang, Huang, and Yang 2020; Frankel and Rose 2005; Grossman and Krueger 1991, 1995; Levinson 2023; Shapiro 2021). The liberalization of trade and investment flows strengthens the incentives for 'environmental dumping' (Grossman and Krueger 1991, 1995). About 20–30% of total CO_2 emissions, which account for most GHG emissions, are estimated to be associated with international trade (World Trade Organization 2022). The effects of trade on the pollution emission of domestic production traverse through scale, composition and technique effects. The net effects could be positive or negative, depending upon environmental regulations (Kirkpatrick and Scrieciu 2008). The environmental regulation and enforcement endeavours are asymmetric across developed (with stringent environmental regulations) and developing (with lax or lenient environmental regulations) countries. Strict environmental regulations (pollution taxes) in developed countries cause pollution-intensive industries to relocate to the developing countries (so-called Pollution Havens) with relatively lax or non-existent environmental regulations (Bu, Lin, and Zhang 2016; Honma and Yoshida 2020; Shapiro and Walker 2018). This leads to environmental leakage in terms of carbon offshoring and pollution outsourcing to the developing countries that manufacture goods for exports to the developed countries.

The import tariff and non-tariff barriers tend to be substantially lower on dirty industries (defined in terms of carbon dioxide emissions per dollar of output) than on clean industries in most countries. This difference in trade policy creates a global implicit subsidy to carbon dioxide emissions in internationally traded goods and contributes to climate change (Shapiro 2021). Empirical studies, however, have conflictingly shown both favourable (Antweiler, Copeland, and Taylor 2001; Cherniwchan 2017; Dean 2002; Frankel and Rose 2005; Hua, Lu, and Zhao 2022) and unfavourable (Liddle 2001; Wood et al. 2018) effects of international trade on environmental quality.

The major concern with EKC empirics is the methodology employed to estimate the model, notwithstanding the diversity of evidence. The EKC model inherently involves the inclusion of a quadratic (and cubic) regressor of income (denoted as say x) to trace the polynomial pattern of the relationship. The level of income, x, is potentially non-stationary and integrated of order d, I(d); where $d \geq 1$. As a result, the quadratic (second order) and/or cubic (third order) transformations of the I(d) series of income, x, make the data generating process (DGP) explosive (without tending to revert to its mean level) and thereby provide spurious estimates of EKC model. Consider a time series, $x(\mathrm{t})$, with DGP represented by a first-order autoregressive (AR) process such that $x(t) = \alpha + \beta x(\mathrm{t}-1)$; error term, $\varepsilon(t)$, is omitted for simplicity. The DGP of a squared AR process can be represented as

$[x(t)]^2 = [\alpha + \beta x(\mathrm{t}-1)]^2 = \alpha^2 + \{\beta x(\mathrm{t}-1)\}^2 + 2\alpha\beta x(\mathrm{t}-1)$. Similarly, the DGP of a cubed AR process can be expressed as $[x(t)]^3 = [\alpha + \beta x(\mathrm{t}-1)]^3 = \alpha^3 + \{\beta x(\mathrm{t}-1)\}^3 + 3\alpha^2\beta x(\mathrm{t}-1) + 3\alpha\{\beta x(\mathrm{t}-1)\}^2$. If $x(\mathrm{t})$ series has a unit root and is integrated of order d so that $d \geq 1$, then the DGP of a non-linear (squared or cubed) series of $x(\mathrm{t})$ would be characterized by a substantially different or complex asymptotic behaviour. The integration and cointegration properties of the quadratic (inverted U-shaped) and cubic (N-shaped) polynomial regressors of income, x, will be discernibly different from those of the standard time-series variables in levels. Therefore, the unit root and cointegration tests performed on the quadratic and cubic regressors of income used in EKC models will provide spurious and misleading evidence.

Economic development is inherently a long-term process; as such, the empirical analysis of the EKC requires the estimation of models over long time horizons. The empirical research, however, is dominated by cross-country studies based on cross-sectional and panel data models. These models are commonly estimated on short time spans and thus are unable to take a temporally secular account of the evidence. The growth structures, production technologies, CO_2 (and other GHG) emissions, environmental regulations and EKC stages are heterogenic across countries. Therefore, the parameter estimates obtained from cross-sectional and panel data models are useful for the sample-group, but they lose relevance for the formulation of country-specific policies.

Regardless of the econometric approach (cross-sectional, time series or panel data) employed to estimate the model, previous research has mainly focused on EKC-type smooth and continuous relationship between income and emissions. It precluded the possibilities of structural breaks or regime switches, which are better approximations of the emission – income relationship. Those few studies that attempt to accommodate structural breaks (Friedl and Getzner 2003; Liddle and Messinis 2015) do not extend beyond examining, at the most, two breaks, and they focus solely on long-period breaks, ignoring the likelihoods of short-period breaks. It is important to test for multiple structural breaks that could occur over long as well as short time periods to have a tenable account of the evidence.

IV. Model specification and data

Model specification

The study draws on the extant literature and specifies the long-run model for the effects of income and control variables on CO_2 emissions (Antweiler, Copeland, and Taylor 2001; Frankel and Rose 2005; Grossman and Krueger 1991, 1995; Harbaugh, Levinson, and Wilson 2002; Holtz-Eakin and Selden 1995; Shapiro 2021). The model is specified without quadratic and higher-order polynomial regressors of income for the reasons discussed in previous sections.

$$\ln CO_2(t) = \alpha + \beta \ln GDP(t) + \gamma' X(t) + \varepsilon(t) \quad \mathrm{t} \in [1, \ldots, \mathrm{T}] \qquad (1)$$

Model (1) is estimated on annual data from India for the period 1951–52 to 2015–2016. The logarithmic scales of the variables used in Model (1) are useful to dampen the variability of data (and outlying observations), smooth the skewness, filter the exponential trend patterns, reduce the heteroscedasticity (variance) of residuals, make the data more normal (symmetric) and improve the linearity between regressand and regressors.

Data and some stylized visualizations

The carbon dioxide, CO_2, emissions in Model (1) are measured in billion tonnes. The real gross domestic product (GDP) is the primary variable, and it is measured at factor cost at 2004–05 prices (Rupees billion). X is a $\mathrm{n} \times 1$ column vector of control variables – financial development (FD), trade openness (TO), and real gross domestic capital formation (GDCF) – and γ is a $\mathrm{n} \times 1$ column vector of the coefficients of controls.

The study draws on Goldsmith (1969, 1983) and measures financial development, FD, in terms of finance ratio. The finance ratio is the ratio of total issues (primary securities plus secondary securities) to nominal national income (net national product at factor cost at current prices). The trade openness, TO, is measured in terms of exports (X) plus imports (M) as a percentage of GDP at market prices such that $TO = [(X + M)/GDP] \times 100$; all at current prices. The real gross domestic capital formation, GDCF, represents domestic investment and it is measured at 2004–05 prices (Rupees billion).

The scatterplot and the time trajectories of the model variables are shown in Figure 1. The boxplots of the variables are depicted in Figure 2. The boxplots provide a visual account of the statistical properties of the model variables in terms of range (minimum to maximum), median, quartiles and inter-quartile range. The lower-end of the box represents the first quartile, the upper-end the third quartile and the middle band the second quartile (median). The lower extremum of the whisker represents the minimum, and the upper extremum shows the maximum of the underlying series. The whiskers extending vertically from boxes within each plot measure the extents of variability outside the lower and upper quartiles of the data series. The boxplots suggest that the distributions differ across variables (Figure 2).

All the data are sourced from the (i) Reserve Bank of India Bulletin, and Handbook of Statistics on the Indian Economy, Reserve Bank of India; (ii) National Accounts Statistics, Central Statistical Organisation; (iii) World Development Indicators (Online), The World Bank; and (iv) Our World in Data (Online), Oxford Martin Programme on Global Development, University of Oxford, and the Global Change Data Lab.

V. Empirical results

Unit root tests

The unit root tests are performed to examine the time-series properties of the model variables. The asymptotically powerful Dickey-Fuller (DF)-GLS and DF-GLSu tests of Elliott, Rothenberg, and Stock (1996) and Elliott (1999), based on generalized least squares (GLS), do not reject the null hypothesis of a unit root for the series in levels, but reject the null hypothesis for most of the series in their first-difference (Table 4). The structural break unit root tests of Lumsdaine and Papell (1997) and Lee and Strazicich (2003, 2004) cross-validate the evidence and generally do not reject the null hypothesis of a unit root for the series in levels, but reject the null hypothesis for the series in their first-difference (Table 4). The unit root analysis points towards I(1) properties of the model variables.

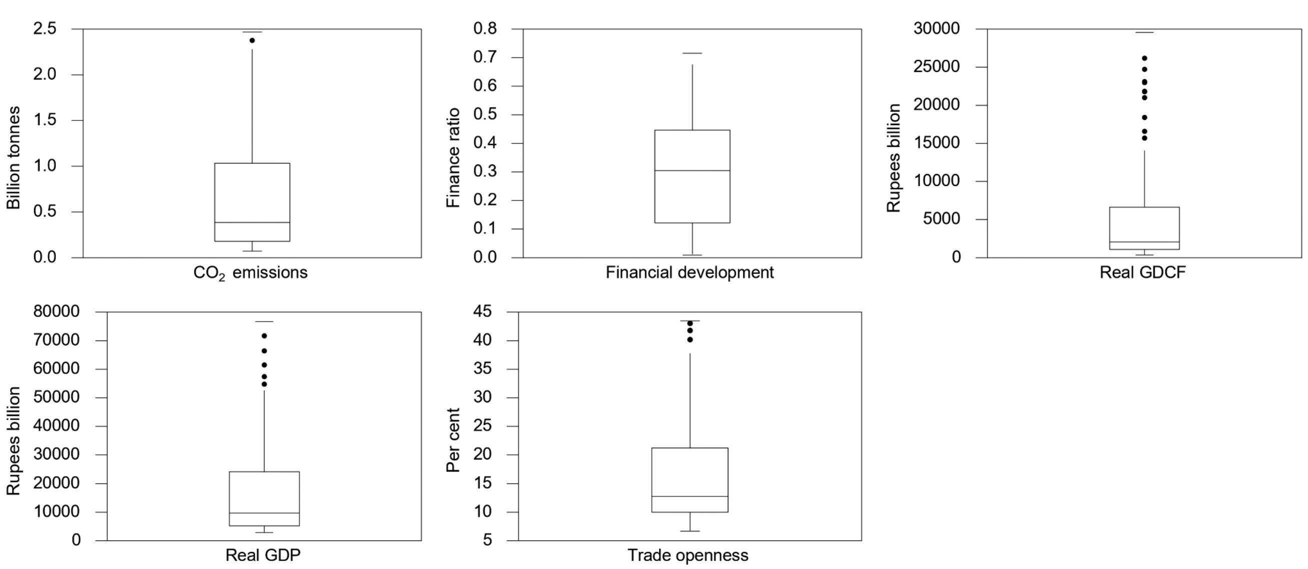

Figure 2. Boxplots of the model variables.

Table 4. Unit root tests.

	No structural break		One structural break		Two structural breaks	
Series	DF-GLS	DF-GLSu	Lumsdaine-Papell	Lee-Strazicich	Lumsdaine-Papell	Lee-Strazicich
			Level series			
$\ln CO_2$	−2.22 (0)	−2.23 (0)	−4.15 (3) [1984]	−4.25 (11) [1974]	−4.47 (3) [1977, 2000]	−5.49* (11) [1976, 1997]
lnGDP	0.07 (0)	−0.50 (0)	−2.71 (4) [1978]	−3.24 (11) [1987]	−4.74 (4) [1984, 2000]	−4.88 (11) [1977, 1989]
lnFD	−1.30 (6)	−1.04 (6)	−8.65*** (2) [1974]	−2.88 (2) [1977]	−9.38*** (2) [1974, 2005]	−3.97 (0) [1970, 1982]
lnTO	−1.13 (2)	−1.40 (2)	−4.35 (1) [1966]	−3.80 (6) [1972]	−5.05 (1) [1966, 1982]	−5.32* (9) [1973, 2002]
lnGDCF	−0.70 (4)	−0.89 (4)	−4.14 (0) [1990]	−3.39 (5) [1991]	−5.23 (0) [1966, 2003]	−5.49* (7) [1981, 2002]
			First-differenced series			
$\Delta\ln CO_2$	−3.39 (2)	−3.37 (2)	−9.71*** (0) [1963]	−8.82*** (0) [2005]	−10.80*** (0) [1963, 1996]	−9.79 (0) [1981, 2001]
ΔlnGDP	−9.72*** (0)	−9.72** (0)	−6.27*** (3) [1964]	−7.96*** (0) [1970]	−7.32*** (3) [1964, 2004]	−8.56*** (0) [1977, 1988]
ΔlnFD	−4.92*** (1)	−5.51** (1)	−7.68*** (1) [1961]	−9.61*** (0) [2007]	−7.89*** (1) [1961, 1977]	−11.30*** (0) [1974, 2005]
ΔlnTO	−4.53*** (0)	−5.80** (0)	−7.36*** (0) [2003]	−5.40*** (0) [1976]	−7.59*** (0) [1970, 2003]	−6.94*** (0) [1975, 2002]
ΔlnGDCF	−5.32*** (0)	−7.39** (0)	−9.83*** (0) [2002]	−7.53*** (0) [1970]	−10.05*** (0) [1975, 2002]	−8.12*** (0) [1970, 2005]

(1) DF-GLS and DF-GLSu tests are the Dickey-Fuller (DF) tests, based on generalized least squares (GLS), developed by Elliott, Rothenberg, and Stock (1996) and Elliott (1999). All tests are performed including a constant and a trend in the model; (2) Figures in parentheses are autoregressive (AR) lags. Figures in square brackets are the breakpoints (break years); (3) Lag-length is determined using the (i) modified Akaike information criterion for the DF-GLS and DF-GLSu tests, (ii) Akaike information criterion for the Lumsdaine-Papell test and (iii) general-to-specific approach for the Lee-Strazicich test; (4) ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Baseline one-regime estimates

Optimal single-equation estimates

The single-equation econometric models suffer from endogeneity and an omitted variable (misspecification) bias of a larger or lesser degree, as these models do not incorporate the full list of regressors. The commonly used method to alleviate endogeneity is the instrumental variables (IV) or generalized method of moments (GMM) estimator of Hansen (1982). The GMM has desirable properties in large samples. The efficiency of the IV or GMM estimator, however, hinges heavily on the quality (weak or strong) and validity (orthogonality) of instruments. Those instruments that are weakly related to endogenous regressors (weak instruments) and are non-orthogonal to the Gaussian disturbances (invalid instruments) can still produce biased and inconsistent estimates. The dynamic OLS (DOLS) estimator of Saikkonen (1991) and Stock and Watson (1993), the non-linear least squares (NLLS) estimator of Phillips and Loretan (1991) and the Fully Modified OLS (FMOLS) estimator of Phillips and Hansen (1990) resolve the endogeneity of regressors and the serial-correlation of residuals and provide unbiased and consistent estimates of the model parameters.

The DOLS estimator augments the standard long-run model in levels with the lags and leads of ΔX(t).

$$Y(t) = \alpha + \beta X(t) + \sum_{j=-k}^{k} \delta(j)\Delta X(t-j) + \xi(t) \tag{2}$$

The lags and leads of ΔX(t) resolve the endogeneity of X(t); however, they do not necessarily eliminate all serial-correlation and heteroscedasticity in ξ(t). Phillips and Loretan (1991) suggest augmenting model (2) with the lagged levels of $[Y(t) - \alpha - \beta\, X(t)]$.

$$Y(t) = \beta_0 + \beta X(t) + \sum_{j=-k}^{k} \delta(j)\Delta X(t-j) + \sum_{j=1}^{k} \varphi(j)[Y(t-j) - \alpha - \beta X(t-j)] + \zeta(t) \tag{3}$$

Model (3) can be estimated using the non-linear least squares (NLLS) estimator. Both DOLS and NLLS are unbiased and asymptotically efficient.

The study estimates Model (1) using the GMM, DOLS, NLLS and FMOLS estimators. The estimations are carried out using the lags and leads structure of k = {−2, 0, +2} for the DOLS and of k = {−3, 0, +3} for the NLLS estimator. The results point towards the (i) positive and significant effects of GDP and financial development, FD, and the (ii) negative and significant effects of trade openness, TO, and domestic investment, GDCF, on CO_2 emissions (Table 5). The elasticity coefficients are consistent across estimators in terms of their numerical magnitudes and statistical significance. Higher GDP and financial development lead to the degradation, while higher trade openness and domestic investment to the improvement in environmental quality.

Table 5. Optimal single-equation estimates of the model.

Independent variable	Dependent variable: $\ln CO_2$			
	GMM	DOLS	NLLS	FMOLS
Constant	−9.54*** (−13.24)	−11.81*** (−12.44)	−9.58*** (−6.44)	−10.84*** (−13.01)
lnGDP	1.29*** (5.89)	1.86*** (7.01)	1.61*** (5.61)	1.50*** (6.76)
lnFD	0.41*** (5.07)	0.31*** (6.23)	0.39*** (5.70)	0.28*** (5.46)
lnTO	−0.30*** (−5.68)	−0.32*** (−4.41)	−0.25** (−2.20)	−0.25*** (−2.92)
lnGDCF	−0.25 (−1.32)	−0.66*** (−3.23)	−0.67*** (−4.32)	−0.38** (−2.26)

(1) Figures in parentheses are t-values; (2) *** and ** indicate statistical significance at 1% and 5% levels, respectively; (3) $J = 2.11$ (p-value = 0.72) in GMM; (4) The estimates of first-differenced lag, contemporaneous and lead dynamic regressors in DOLS and NLLS are not reported to conserve space.

ARDL-ECM estimates

The conditional error-correction model (ECM) based on the autoregressive distributed lag (ARDL) model of Pesaran, Shin, and Smith (2001) is useful to examine the long-run relationship among variables with different orders of integration. The ARDL – ECM augments the standard short-run ARDL model in first-difference with lagged regressors in levels and then tests the null hypothesis of zero-restrictions on the parameters of these augmented lagged-level regressors.

$$\begin{aligned}\Delta \ln CO_2(t) = {}& \gamma_0 + \sum_{i=1}^{k} \xi(i)\Delta \ln CO_2(t-i) \\ & + \sum_{i=1}^{k} \zeta(i)\Delta \ln GDP(t-i) \\ & + \sum_{i=1}^{k} \phi(i)\Delta \ln FD(t-i) \\ & + \sum_{i=1}^{k} \psi(i)\Delta \ln TO(t-i) \\ & + \sum_{i=1}^{k} \gamma(i)\Delta \ln GDCF(t-i) \\ & + \begin{bmatrix} \delta_1 \ln CO_2(t-1) + \delta_2 \ln GDP(t-1) \\ + \delta_3 \ln FD(t-1) + \delta_4 \ln TO(t-1) \\ + \delta_5 \ln GDCF(t-1) \end{bmatrix} + \varepsilon(t) \end{aligned} \tag{4}$$

The joint F-test is used to test $H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ (no cointegration) against H_1: at least one $\delta_i \neq 0$, i = 1, 2, . . ., 5 (cointegration). The asymptotic distribution of the F statistic is non-standard. Pesaran, Shin, and Smith (2001) provide upper bound – if regressors are I(1) – and lower bound – if regressors are I(0) – critical values for the non-standard F statistic to test the null hypothesis of no cointegration among the I(d) variables, where $0 \leq d \leq 1$. The lag structure, k, in model (4) is selected such that there is no serial-correlation in the model residuals, as suggested by the Ljung – Box Q (LB – Q) statistic (Ljung and Box 1978). The standard errors of the parameters are adjusted using the HAC estimator.

$$\begin{aligned}\Delta \ln CO_2(t) = {}& \underset{(-2.40)}{-1.6324^{**}} \\ & + \sum_{i=1}^{5} \underset{[4.67]}{0.1094^{***}} \Delta \ln CO_2(t-i) \\ & + \sum_{i=1}^{5} \underset{[1.42]}{0.1498} \Delta \ln GDP(t-i) \\ & - \sum_{i=1}^{5} \underset{[3.82]}{0.1825^{***}} \Delta \ln FD(t-i) \\ & - \sum_{i=1}^{5} \underset{[1.51]}{0.0344^{*}} \Delta \ln TO(t-i) \\ & + \sum_{i=1}^{5} \underset{[1.38]}{0.2039} \Delta \ln GDCF(t-i) \\ & \underset{(-3.50)}{-0.2072^{***}} \ln CO_2(t-1) + \underset{(2.11)}{0.2476^{**}} \ln GDP(t-1) \\ & + \underset{(4.06)}{0.1107^{***}} \ln FD(t-1) \underset{(-0.29)}{-0.0086} \ln TO(t-1) \\ & \underset{(-1.36)}{-0.0818} \ln GDCF(t-1) \end{aligned} \tag{5}$$

$R^2 = 0.5043$; DW = 1.97; LB – Q{16} = 16.01, p-value = 0.45
$H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$;
H_1: at least one $\delta_i \neq 0$, i = 1, 2, . . ., 5
F-statistic = 7.1633

Figures in parentheses in Equation (5) are the t-values. Figures in square brackets are the F-statistics for the joint null hypothesis of zero-restrictions on the summarized parameters of the first-differenced dynamic regressors. The joint F-statistic = 7.1633 strongly rejects the null hypothesis (at the 1% level) and suggests the presence of cointegration among the level variables.

The estimates of ARDL – ECM (5) are used to derive the parameters of the long-run model.

Table 6. Maximum-likelihood system estimates of the model [VAR lag, k = 5].

	λ-trace statistics				λ-max statistics			
Eigenvalues	H_0	H_1	λ-trace	95% CV	H_0	H_1	λ-max	95% CV
0.461	r = 0	r ≥ 1	77.321**	68.52	r = 0	r = 1	37.03**	33.46
0.279	r ≤ 1	r ≥ 2	40.292	47.21	r ≤ 1	r = 2	19.61	27.07
0.200	r ≤ 2	r ≥ 3	20.682	29.68	r ≤ 2	r = 3	13.36	20.97
0.112	r ≤ 3	r = 4	7.318	15.41	r ≤ 3	r = 4	7.15	14.07
0.003	r ≤ 4	r = 5	0.172	3.76	r ≤ 4	r = 5	0.17	3.76

	Long-run parameters of the first cointegrating vector normalized on $lnCO_2$					
	$lnCO_2$	lnGDP	lnFD	lnTO	lnGDCF	95% χ^2
Long-run coefficients	1***	−1.827***	−0.343**	0.484***	0.697**	
Likelihood ratio test of exclusion restrictions	(8.875) [0.003]	(7.066) [0.008]	(5.254) [0.022]	(10.216) [0.001]	(4.207) [0.040]	3.841

(1) r denotes the number of cointegrating vectors; (2) CV denotes critical values; (3) Figures in parentheses are χ^2 values for the null hypothesis of exclusion restrictions on long-run coefficients. Figures in square brackets are p-values; (4) *** and ** indicate statistical significance at 1% and 5% levels, respectively.

$$\ln CO_2 = \omega_0 + \omega_1 \ln GDP + \omega_2 \ln FD + \omega_3 \ln TO + \omega_4 \ln GDCF \quad (6)$$

where $\omega_0 = -\left[\frac{\gamma_0}{\delta_1}\right]$ and $\omega_i = -\left[\frac{\delta_i}{\delta_1}\right]; i \in \{2, 3, 4, 5\}$.

The estimates of the long-run model (6) are as follows.

$$\ln CO_2 = \underset{(-4.42)}{-7.8764^{***}} + \underset{(2.94)}{1.1949^{***}} \ln GDP + \underset{(5.39)}{0.5343^{***}} \ln FD \underset{(-0.31)}{-0.0414} \ln TO \underset{(-1.44)}{-0.3949} \ln GDCF \quad (7)$$

Model (7) provides strong support for the positive and significant long-run effects of GDP and financial development on CO_2 emissions. Higher GDP and financial development lead to higher CO_2 emissions. By contrast, higher trade openness, TO, and domestic investment, GDCF, reduce CO_2 emissions and lead to the improvement in environmental quality.

Maximum-likelihood system estimates

The maximum-likelihood (ML) system estimator of Johansen (1991) estimates the k^{th} order vector autoregression (VAR) model and takes a system-based account of endogeneity. The ML estimates suggest the presence of one cointegrating vector. Both λ-trace and λ-max statistics reject the null hypothesis of $r = 0$, but not the null hypothesis of $r \leq 1$, at the 5% level (Table 6). The results reinforce the positive effects of GDP and financial development and the negative effects of trade openness, TO, and domestic investment, GDCF, on CO_2 emissions. Higher GDP and financial development lead to the degradation, while higher trade openness and domestic investment to the improvement in environmental quality.

Over-parameterized level-VAR estimates

The system-based counterpart of the single-equation ARDL-ECM is the over-parameterized level-VAR estimator of Toda and Yamamoto (1995). The TY estimator estimates the VAR system with stationary or integrated or cointegrated processes of an arbitrary order.

$$\begin{bmatrix} \ln CO_2(t) \\ \ln GDP(t) \\ \ln FD(t) \\ \ln TO(t) \\ \ln GDCF(t) \end{bmatrix} = \omega + \sum_{i=1}^{k} \xi(i) \begin{bmatrix} \ln CO_2(t-i) \\ \ln GDP(t-i) \\ \ln FD(t-i) \\ \ln TO(t-i) \\ \ln GDCF(t-i) \end{bmatrix} + \sum_{i=k+d}^{d\,max} \xi(i) \begin{bmatrix} \ln CO_2(t-i) \\ \ln GDP(t-i) \\ \ln FD(t-i) \\ \ln TO(t-i) \\ \ln GDCF(t-i) \end{bmatrix} + \begin{bmatrix} \varepsilon_1(t) \\ \varepsilon_2(t) \\ \varepsilon_3(t) \\ \varepsilon_4(t) \\ \varepsilon_5(t) \end{bmatrix} \quad (8)$$

The study estimates three sets of over-parameterized level-VAR model (8) – one based on dmax = 0 (Model I), the second on dmax = 1 (Model II) and the third on dmax = 2 (Model III). The lag structure is selected such that there is no serial-correlation in the model residuals, as suggested by the LB – Q statistics. The joint F statistics computed for first k = 4 lags reject the null hypothesis of zero restrictions on the parameters of the lagged regressors of GDP and financial development, FD, in all the models estimated with $\ln CO_2$ as the dependent variable (Table 7). The F statistics do not reject the null hypothesis of zero restrictions on the parameters of

Table 7. Over-parameterized level-VAR estimates of the model [F-statistics].

Lagged Regressor	Dependent variable lnCO$_2$	lnGDP	lnFD	lnTO	lnGDCF
Model I: dmax = 0; VAR lags: q = [k + dmax] = [4 + 0] = 4; zero-restrictions for first k = 4 lags					
lnCO$_2$	92.58*** (0.00)	3.85*** (0.00)	0.60 (0.67)	1.55 (0.18)	1.14 (0.33)
lnGDP	2.73** (0.03)	24.71*** (0.00)	2.91** (0.02)	0.24 (0.92)	3.53*** (0.007)
lnFD	4.65*** (0.00)	3.30*** (0.01)	3.44*** (0.008)	4.12*** (0.00)	2.87** (0.02)
lnTO	4.38*** (0.00)	6.01*** (0.00)	5.322*** (0.00)	60.88*** (0.00)	2.34** (0.05)
lnGDCF	1.10 (0.36)	2.08* (0.08)	0.32 (0.87)	4.95*** (0.00)	10.09*** (0.00)
Model II: dmax = 1; VAR lags: q = [k + dmax] = [4 + 1] = 5; zero-restrictions for first k = 4 lags					
lnCO$_2$	43.01*** (0.00)	6.32*** (0.00)	1.33 (0.26)	1.58 (0.18)	0.77 (0.55)
lnGDP	2.77** (0.03)	9.46*** (0.00)	4.88*** (0.00)	2.14* (0.07)	1.47 (0.21)
lnFD	3.02** (0.02)	5.17*** (0.00)	10.01*** (0.00)	3.19*** (0.01)	3.09** (0.015)
lnTO	1.63 (0.16)	11.46*** (0.00)	3.74*** (0.00)	19.77*** (0.00)	0.62 (0.65)
lnGDCF	1.29 (0.27)	1.90 (0.11)	1.30 (0.27)	2.83** (0.02)	12.07*** (0.00)
Model III: dmax = 2; VAR lags: q = [k + dmax] = [4 + 2] = 6; zero-restrictions for first k = 4 lags					
lnCO$_2$	21.57*** (0.00)	5.50*** (0.00)	3.23*** (0.012)	1.51 (0.20)	3.19*** (0.01)
lnGDP	2.39** (0.049)	7.66*** (0.00)	6.17*** (0.00)	1.25 (0.29)	2.88** (0.02)
lnFD	3.24*** (0.01)	3.19*** (0.01)	14.31*** (0.00)	2.45** (0.04)	0.82 (0.51)
lnTO	1.87 (0.11)	4.20*** (0.00)	2.53** (0.04)	11.60*** (0.00)	0.98 (0.42)
lnGDCF	1.94 (0.10)	2.02* (0.09)	4.49*** (0.001)	5.71*** (0.00)	19.67*** (0.00)

(1) Figures in parentheses are p-values; (2) ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively; (3) Some of the p-values are on the border line of critical region.

the lagged regressors of trade openness, TO, and domestic investment, GDCF, in both Model II and Model III. The results provide strong support for the significant effects of the primary variable, GDP, on CO_2 emissions.

Structural breaks

The structural breaks reduce the power of cointegration tests and weaken the robustness of statistical evidence obtained from one-regime models with time-invariant parameters and no structural break. Several factors, including random shocks to technology, spurt or slump in economic growth, and adoption of endogenous environmental policies to control carbon and other GHG emissions, could cause structural breaks in the equilibrium relationship and model parameters. This section extends the analysis and estimates the model in the presence of structural breaks.

Long-period breaks

Bai and Perron (1998, 2003) consider a linear model and use a dynamic programming algorithm to determine m number of unknown breaks and the implied $m + 1$ number of regimes. Kejriwal and Perron (2008, 2010) allow I(1) as well as I(0) regressors in the cointegrating model. They suggest conducting three tests to determine m number of unknown breaks and the implied $m + 1$ number of regimes – (i) the Sup-Wald test for the null hypothesis of no structural break $(m = 0)$ against $m = L$ number of arbitrarily fixed breaks, (ii) the double maximum (UDmax) test for the null hypothesis of no structural break $(m = 0)$ against an unknown number of breaks between one and some upper bound M, such that $1 \leq M$ and (iii) the sequential $SEQ_T(L + 1)/L$ test for the null hypothesis of L against the alternative hypothesis of $L + 1$ breaks. They suggest using the linear DOLS estimator of Saikkonen (1991) and Stock and Watson (1993) to resolve the endogeneity of regressors and serial-correlation of residuals. The limiting distributions of the tests based on DOLS are the same as those obtained with static regression under strict exogeneity.

The study performs Kejriwal – Perron tests on the DOLS model (2), estimated using the lags and leads structure of k = {−2, 0, +2}, and endogenously determines structural breaks in the equilibrium relationship and model parameters. The Sup-F(m) test rejects the null hypothesis of no structural break $(m = 0)$ against the alternative hypothesis of $m = L = 3$ breaks. Both UDmax and $SEQ_T(L + 1)/L$ statistics consistently reject the null hypothesis of $L = 2$ breaks and suggest the presence of three breaks (Table 8). The RSS, BIC and LWZ statistics are consistently minimized at $L = 3$ breaks, suggesting the presence of three breaks, where RSS stands for the residual sum of squares, BIC: Bayesian information criterion of

Table 8. Kejriwal – Perron tests for multiple structural breaks.

Panel I: Test criteria				
Break		RSS (L)	BIC (L)	LWZ (L)
0		0.07385	−4.41	−3.00
1		0.05058	−4.38	−2.58
2		0.00721	−5.92	−3.64
3		0.00063	−7.95	−5.01
		Critical values		
Test	Test statistics	1%	5%	10%
Panel II: Sup-F(m) test: $H_0 : m = 0; H_1 : m = L$				
Sup-F(1|0)	1.56	22.59	19.08	16.87
Sup-F(2|0)	11.10	18.85	15.90	14.72
Sup-F(3|0)	54.64***	16.44	14.15	13.20
Panel III: Sequential $SEQ_T(L+1)/L$ test: H_0 : L breaks; H_1 : L + 1 breaks				
Sup-F(1|0)	1.56	25.73	20.80	18.96
Sup-F(2|1)	22.19**	27.01	21.59	19.91
Sup-F(3|2)	163.91***	27.43	22.36	20.68
L number of structural breaks based on various test statistics and minimized criteria				
UDmax (L)	Sup-F	RSS (L)	BIC (L)	LWZ (L)
54.64*** (3)	163.91*** (3)	0.00063 (3)	−7.95 (3)	−5.01 (3)
Panel IV: Breakpoints and the 95% confidence intervals				
	Breakpoints	95% confidence bands		
Number of breaks	(Break years)	Lower band	Upper band	
m = 1	1975	1974	1976	
m = 2	1983	1982	1984	
m = 3	1991	1990	1992	
Panel V: Parameter estimates by regime				
Shifting regressors	Regime 1 [≤1975]	Regime 2 [≤1983]	Regime 3 [≤1991]	Regime 4 [>1991]
Constant	−2.13	1.78	−17.15	−6.16
lnGDP	0.61	0.38	2.72	1.12
lnFD	1.24	0.90	0.95	1.00
lnTO	−0.50	−0.50	−0.86	−0.51
lnGDCF	−0.17	−0.52	−0.74	−0.31

(1) Figures in parentheses are L number of structural breaks; (2) *** and ** indicate statistical significance at 1% and 5% levels, respectively; (3) RSS stands for residual sum of squares, BIC: Bayesian information criterion of Yao (1988), and LWZ: modified Schwarz information criterion of Liu et al. (1997).

Yao (1988), and LWZ: modified Schwarz information criterion of Liu, Wu, and Zidek (1997). The endogenously determined breakpoints are 1975, 1983 and 1991. The coefficient of the primary regressor, GDP, remains algebraically positive, but shifts numerically across regimes.

Short-period breaks

The power of the standard structural break estimators tends to decline as the breakpoint moves towards the end of the sample space. This section uses the end-of-sample cointegration breakdown tests of Andrews and Kim (2006) and examines the cointegrating relationship in the presence of short-period breaks. These tests involve splitting the total sample size, $t = 1, \ldots, T + m$, into first T and last m observations and then estimating the model,

$$y_t = \begin{cases} x_t'\beta_0 + u_t; & t \in \{1, \ldots, T\} \\ x_t'\beta_t + u_t; & t \in \{T+1, \ldots, T+m\} \end{cases} \tag{9}$$

Under the null hypothesis, the model is a well-specified cointegrating regression for all $t \in \{1, \ldots, T + m\}$.

$$H_0: \begin{cases} \beta_t = \beta_0 \text{ for all } t = T+1, \ldots, T+m \text{ and} \\ \{u_t: t = 1, \ldots, T+m\} \text{ are stationary and ergodic} \end{cases}$$

Under the alternative hypothesis, the model is a well-specified cointegrating regression for all $t \in \{1, \ldots, T\}$, but the cointegration breaks down for $t \in \{T + 1, \ldots, T + m\}$.

$$H_1: \begin{cases} \beta_t \neq \beta_0 \text{ for some t} \in \{T+1,\ldots,\mathrm{T}+m\} \\ \text{and/or the distribution of} \\ \{u_{T+1},\ldots,\mathrm{u}_{T+m}\} \text{ differs from the} \\ \text{distribution of } \{u_1,\ldots,\mathrm{u}_m\} \end{cases}$$

The null hypothesis that cointegration prevails for the full sample period is tested against the alternative hypotheses of cointegration breakdowns during several sub-sample periods using the sets of $P \in \{P_a,\mathrm{P}_b,\mathrm{P}_c\}$ and $R \in \{R_a,\mathrm{R}_b,\mathrm{R}_c\}$ tests. These tests are performed on the OLS, FMOLS and Full-Information Maximum-Likelihood (FIML) system estimates of the model. The choice of the best test is not unambiguously clear. On balance, Andrews and Kim (2006) prefer P_c because of its somewhat better size properties, compared to R_c.

Both P_c and R_c tests provide dominant support for the presence of cointegration among the level variables (Table 9). The long-run coefficients suggest the positive effects of GDP and financial development and the negative effects of trade openness on CO_2 emissions, consistently across all sub-sample periods. The GDCF generally has negative effects on CO_2 emissions. The numerical magnitudes of the coefficients of GDP and control variables vary across sub-sample periods.

VI. Discussion and policy perspectives

The stylized precursor provides robust support for the positive and significant effects of GDP and financial development and for the negative effects of trade openness and domestic investment on CO_2 emissions. The results resonate with several studies suggesting the adverse effects of economic growth on environmental quality (Azomahou, Laisney, and Nguyen 2006; Fang, Huang, and Yang 2020; Magazzino 2024; Richmond and Kaufmann 2006; Shafik 1994; Yu et al. 2022). Developing countries face the dual challenges of acceleration in economic growth and reduction in CO_2 emissions. Unregulated emissions create a moral hazard problem among emitters, given that environment is both a common resource and a non-excludable public good. The markets are unable to internalize the external costs of production in terms of negative externalities and thus are unable to capture all costs in prices.

The emission abatement is unlikely to emerge endogenously from economic growth and market-based incentives. Policy intervention, in terms of the imposition of Pigouvian tax (*a la* Pigou 1920), allocation of carbon emission permits (quotas) and promotion of carbon 'cap-and-tax' and/or carbon 'cap-and-trade' systems, is needed to correct market failure, to cover the external costs of pollution and to curtail the emission of carbon. The carbon tax embodies both corrective incentives and penalties. A carbon tax higher than the cost of employing carbon-efficient technologies would provide strong incentives to firms to adopt carbon-efficient technologies or switch to cleaner renewable energy. An increasing body of empirical studies has shown that carbon taxes can effectively reduce carbon emissions, or at least dampen their growth, while not negatively affecting economic growth, employment and competitiveness (Köppl and Schratzenstaller 2023). India pursued a '*de facto*' carbon tax system under which subsidies were reduced and heavy excise duties were imposed on fossil fuels to monetize the damages from carbon emissions and to make polluters bear financial burden and internalize the costs of their polluting activities. Such a '*de facto*' tax needs to be complemented by a '*de jure*' direct tax on carbon.

The carbon 'cap-and-trade' system or emission trading scheme (ETS) involves setting a maximum limit on pollution and distributing emission permits among carbon emitting firms. The emission permits created by an environment regulatory authority would provide financial incentives to firms to pollute less, as they could sell their excess permits to other firms either directly through a peer-to-peer trading or indirectly through a secondary market mechanism. The glut of permits in the market is unlikely to deliver efficient outcomes, given that the supply of permits more than their efficient number would lead to trading permits at prices that are not high enough to encourage emission abatement. Therefore, it is important to ensure that the efficient number of emission permits made available for trading is equal to the efficient quantity of emission. The emission permits would generate carbon revenues for the state. These revenues could be ploughed back in terms of 'green investment' or 'green subsidies' to foster carbon-efficient technologies.

Table 9. End-of-sample cointegration breakdown tests and the estimates of the model parameters [Dependent variable: $lnCO_2$].

H_0: Cointegration prevails for the full sample period from 1951-52 to 2015-16.
H_1: Cointegration breaks down during sub-sample periods.

	Model I			Model II			Model III			Model IV			Model V		
	2000-01 to 2015-16; *m* = 16			2005-06 to 2015-16; *m* = 11			2008-09 to 2015-16; *m* = 8			2010-11 to 2015-16; *m* = 6			2013-14 to 2015-16; *m* = 3		
Test statistics	OLS	FMOLS	FIML	OLS	FMOLS	FIML	OLS	FMOLS	FIML	OLS	FMOLS	FIML	OLS	FMOLS	FIML
P_a	3.60***	2.70***	0.79	1.44***	0.31***	16.38***	0.51***	0.15	10.13	0.36***	0.16	2.63	0.16***	0.09***	0.99***
	(0.00)	(0.00)	(0.16)	(0.00)	(0.07)	(0.10)	(0.02)	(0.22)	(0.28)	(0.06)	(0.15)	(0.16)	(0.02)	(0.10)	(0.02)
P_b	0.63***	0.19**	14.10***	0.44*	0.17	3.99	0.25	0.10	3.22	0.21	0.09	1.83	0.13**	0.05	0.41
	(0.00)	(0.03)	(0.00)	(0.07)	(0.20)	(0.27)	(0.14)	(0.40)	(0.36)	(0.11)	(0.35)	(0.18)	(0.03)	(0.28)	(0.23)
P_c	0.13	0.07	0.44*	0.12	0.05	0.38	0.10	0.04	0.26	0.10	0.03	0.14	0.07	0.03	0.02
	(0.12)	(0.18)	(0.10)	(0.14)	(0.64)	(0.90)	(0.26)	(0.72)	(0.83)	(0.22)	(0.70)	(0.80)	(0.13)	(0.38)	(0.91)
R_a	392.74***	294.61***	84.69	71.34***	14.45**	778.76*	14.28**	3.80	262.21	5.60**	2.48*	41.91	0.77**	0.42**	4.76**
	(0.00)	(0.00)	(0.16)	(0.00)	(0.02)	(0.07)	(0.02)	(0.20)	(0.26)	(0.04)	(0.09)	(0.16)	(0.02)	(0.03)	(0.02)
R_b	66.03***	14.35**	1517.64***	21.93**	7.20	199.85	6.85*	2.03	85.09	3.32*	1.26	29.14	0.63**	0.26	1.93
	(0.00)	(0.03)	(0.00)	(0.02)	(0.16)	(0.17)	(0.08)	(0.28)	(0.30)	(0.07)	(0.28)	(0.16)	(0.03)	(0.15)	(0.23)
R_c	9.66***	0.49	32.40**	5.14***	0.47	11.36	2.62	0.42	3.52	1.46	0.35	1.07	0.34	0.15	0.02
	(0.00)	(0.44)	(0.03)	(0.00)	(0.52)	(0.68)	(0.20)	(0.52)	(0.74)	(0.20)	(0.56)	(0.90)	(0.12)	(0.25)	(0.93)
Model parameters															
$\hat{\beta}_{1-T}$	1951-52 to 1999-2000			1951-52 to 2004-05			1951-52 to 2007-08			1951-52 to 2009-10			1951-52 to 2012-13		
α	−11.9604	−11.7354	−9.8881	−11.1790	−10.1758	−8.0508	−11.7548	−11.5951	−5.4411	−11.7227	−12.3248	−5.1845	−11.6511	−12.2774	−5.8012
βlnGDP	1.1025	1.1326	0.9635	1.0689	1.2180	2.6316	1.3585	1.6653	1.7839	1.3890	1.8314	0.9443	1.4378	1.8907	1.0343
$\gamma_1$lnFD	0.0463	0.0753	0.1870	0.0884	0.2899	0.7832	0.1109	0.2777	0.7999	0.1207	0.2420	0.5322	0.1388	0.2657	0.5083
$\gamma_2$lnTO	−0.1157	−0.1421	−0.0839	−0.1582	−0.2767	−0.2818	−0.2390	−0.2625	−0.3479	−0.2538	−0.2526	−0.1485	−0.2719	−0.2806	−0.1134
$\gamma_3$lnGDCF	0.1627	0.1108	0.0712	0.1191	−0.1121	−1.9861	−0.1221	−0.4692	−1.2829	−0.1564	−0.5826	−0.4302	−0.2151	−0.6456	−0.4700
$\hat{\beta}_{1-[T+(m/2)]}$	1951-52 to 2007-08			1951-52 to 2009-10			1951-52 to 2011-12			1951-52 to 2012-13			1951-52 to 2013-14		
α	−11.7548	−11.5951	−5.4411	−11.7227	−12.3248	−5.1845	−11.6881	−12.2690	−5.4345	−11.6511	−12.2774	−5.8012	−11.4541	−11.8835	−7.9447
βlnGDP	1.3585	1.6653	1.7839	1.3890	1.8314	0.9443	1.4339	1.8885	1.0512	1.4378	1.8907	1.0343	1.4034	1.8312	1.3762
$\gamma_1$lnFD	0.1109	0.2777	0.7999	0.1207	0.2420	0.5322	0.1346	0.2703	0.5422	0.1388	0.2657	0.5083	0.1454	0.2864	0.4237
$\gamma_2$lnTO	−0.2390	−0.2625	−0.3479	−0.2538	−0.2526	−0.1485	−0.2686	−0.2845	−0.1348	−0.2719	−0.2806	−0.1134	−0.2723	−0.2885	−0.1472
$\gamma_3$lnGDCF	−0.1221	−0.4692	−1.2829	−0.1564	−0.5826	−0.4302	−0.2074	−0.6421	−0.5249	−0.2151	−0.6456	−0.4700	−0.1984	−0.6193	−0.6040

(1) OLS stands for Ordinary Least Squares, FMOLS: Fully Modified OLS, and FIML: Full-Information Maximum-Likelihood system estimator; (2) *m* denotes the number of observations in the breakdown periods; (3) FIML estimation is carried out using the VAR lag structure of four; (4) Figures in parentheses are p-values; (5) ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively; (6) Some of the p-values are on the border line of critical region.

The price-based policy instruments are unlikely to be sufficient by themselves to achieve the desired reduction in emission. Both carbon tax and ETS increase the cost of production, which the carbon emitting industries could pass on to consumers in the form of higher prices depending on the price-elasticities of demand for their products. The efficacy of regulatory policies and mitigation strategies is contingent on the causes of pollution. Heavy reliance on the combustion of fossil fuels to generate electric power is a major factor catalytic to continual emission of carbon. The price-based instruments thus need to be accompanied by the progressive development of carbon-efficient technologies and use of carbon-neutral substitutes. It would be useful to promote international trade and benefit from global value chains. It is worth subsidizing alternative sources of energy and stimulating investment in long-term assets linked to cleaner production and green technologies.

VII. Conclusions

This study has taken a robust account of the effects of economic growth on environmental quality in India, historically since the inception of economic planning. India witnessed tremendous transformation from a persistently slow/low growth economy of the 1950s through to the 1970s, to a modest-growth economy of the 1980s, and then to a high-growth economy from the early 1990s. The marginal propensity to emit carbon commensurately remained low until the 1970s, became modest in the 1980s, and then turned higher from the 1990s. The CO_2 emissions are running on their upward trajectory and have not yet reached their maxima.

The baseline model estimated in a one-regime setting with no structural break provides robust support for the positive and significant effects of GDP and financial development and for the negative effects of trade openness and domestic investment on CO_2 emissions. The multiple structural break tests suggest the presence of three breaks and the implied four regimes. The coefficient of the primary variable, GDP, remains algebraically positive but shifts numerically across regimes. The end-of-sample cointegration breakdown tests reinforce the positive effects of GDP on CO_2 emissions. The presence of structural breaks challenges the validity of the EKC-type smooth and continuous relationship between income and emissions postulated in previous research. The evidence drawn from multiple estimators significantly improves our understanding of the emission – income nexus.

The study highlights several opportunities for future research, notwithstanding the voluminous research conducted in this domain. First, the time-series properties and asymptotic behaviour of the variables with quadratic or higher-order polynomials are quite complex. It is important to be cognizant of such complexity when performing unit root and cointegration tests on the quadratic or higher-order polynomial regressors used in EKC models. Second, the reliance on single or select estimators to estimate the model could lead to biased results. It is vital to use a battery of estimators to estimate the model and assess the robustness of results across methodologies. Third, economic development is inherently a long-term process and, as such, the EKC models should be estimated on long, rather than short, time horizons to have a robust assessment of the polynomial pattern of the emission – income trajectory. The regime-switching models would be useful to determine the threshold level of income and thus to trace the transitional path from environmental degradation to environmental improvement. Fourth, the gradient of the bell-shaped emission – income trajectory varies with the level of income. Quantile Regression could be employed to discern the effects of different stages of economic growth on GHG emissions. Finally, environmental regulations are vital complements to the level of income in generating turning point(s) in the emission – income trajectory. It will be useful to construct a composite index of environment-related regulations and policies. This index could be used to have an inclusive assessment of the effects of regulatory policies on environmental quality.

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Data availability statement

The data that support the findings of this study are available from the author upon request.

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