

An Econometric Analysis of Economic Development and CO₂ Emissions in India

Abstract

This study explores the effect of economic growth on India's environmental quality. As indicators of economic development and environmental degradation, respectively, the GDP per capita and CO₂ emissions are utilised. Using the Johansen co-integration test and vector error correction model (VECM), econometric study reveals a long-term correlation between CO₂ emissions, GDP per capita, and industrial value added. Keeping constant the value added to industry, CO₂ emissions grow as per capita GDP rises. India's GDP per capita is found to have a negative correlation with CO₂ emissions. However, assuming no change in GDP per capita, CO₂ emissions increase alongside industrial value addition. In other words, if we adjust for industrial value added, the connection between CO₂ emissions and GDP per capita is a monotonically sloping downward curve, as opposed to the inverted U-shaped curve predicted by Environment Kuznet's Curve. The link between CO₂ emissions and industrial value added is upward-sloping when controlling for per capita GDP. Regardless of its level, a rise in per capita income has a positive effect on environmental quality as long as industrial value added does not increase. Only the downward-sloping portion of Environment Kuznet's Curve is observed without industrial value added expansion. This discovery has significant long-term implications for India. As is typical for a country, when the growth in industrial value added becomes static, any additional economic progress in India will improve the quality of the environment. This suggests the need for environmental policies aimed at reducing emissions during periods of economic growth.

Keywords: CO₂ Emissions; Economic Development; VECM; Long-Run Relationship

Introduction

The environmental Kuznets curve (EKC) postulates that indices of environmental deterioration are high at low levels of development and decrease as the degree of development increases. In other words, it anticipates inverted U-shaped connections between environmental degradation indices and economic progress. The EKC is named after Kuznets (1955), who argued that income inequality increases with economic development until it reaches a particular threshold and then decreases. The EKC concept gained traction in the early 1990s as a result of Grossman and Krueger's (1991) ground-breaking research on the possible effects of NAFTA and the 1992 World Bank Development Report (World Bank, 1992). If the EKC hypothesis were accurate, then, contrary to what the environmental movement and affiliated scientists have argued in the past (Meadows et al., 1972), economic

expansion would be the automatic way to eventual environmental betterment. In 'Our Common Future', published in 1987 by the World Commission on Environment and Development, this shift in perspective was already evident in the concept of sustainable economic development. Clearly, the notion of achieving sustainability without a significant diversion from business as usual was appealing to a great number of individuals – allowing us to "have our cake and eat it too." (Rees, 1990). The EKC is primarily an empirical phenomenon, yet the majority of the research on the EKC is econometrically inadequate. Particularly, the statistical features of the data employed, such as serial dependency or stochastic trends in time-series, and the difficulties of model adequacy, such as the possibility of omitted variables bias, have received minimal discussion. However, one of the primary functions of econometrics is to determine which apparent associations are legitimate and which are erroneous. The EKC does not exist when diagnostic statistics, specification tests, and the relevant methodologies are applied. Instead, a more realistic assessment of the impact of economic expansion and technology advancements on environmental quality is presented. Although the "elasticity of environmental degradation with respect to income" is less than one and not a simple function of income alone, it appears that emissions of most pollutants and waste flows increase monotonically with income (Perman and Stern, 2003). Long-term environmental damage is produced by economic expansion. This relationship revolves upon the reported inverted U-shaped link between output growth and pollution levels. This relationship is known as Kuznet's Curve for the Environment (EKC). Moreover, stricter enforcement of environmentally beneficial government policies raises environmental consciousness and enables the implementation of stricter ecological rules. Thus, the economy shifts toward fewer polluting industries and the development of more environmentally friendly technologies (Panayotou, 1993). Enhanced environmental quality is also believed to be associated with increased economic growth. Several theoretical theories exist for this association. Some believe environmental quality to be a typical good, hence its income elasticity is greater than zero. In other words, as income increases, individuals place a higher value on environmental quality, resulting in more environmental concern (Beckerman, 1992; World Bank, 1992). As affluence rises, so does the opportunity to use more efficient and less polluting capital and technology (Grossman and Krueger, 1995). In addition, when a nation's economic prosperity improves, the proportion of industrial output to total output drops and the proportion of service sector output grows. These sectoral changes benefit the environment as well (Janicke et al., 1997). However, when the proportion of agriculture and industry increases at a lower income level, the total environmental quality declines. In addition, low-

income developing nations are more likely to attract pollution-intensive companies from high-income industrialised nations, a phenomenon known as the "pollution haven hypothesis." As a rural economy gradually transforms into an industrial one, environmental damage is expected to increase in the early stages of development. At a later stage, as the economy shifts from an industrial to a service-based economy, a decline in environmental quality becomes more probable. There are three primary long-term forces that alter the scale and origins of environmental degradation. These three primary factors are changes in economic structure, economic size, and technology. If there is no change in economic structure and technology, the expansion of the economy will lead to a worsening of the environment. This is commonly referred to as scale effect. At higher levels of development, structural changes favouring service sectors, coupled with increased environmental awareness, enforcement of environmental regulations, improved technology, and higher environmental expenditures, result in environmental degradation levelling off and declining gradually (Panayotou, 1993). These immediate or direct causes are in turn decided by environmental rules, awareness, and education. For some components of the ecosystem, there is no turning point. Examples include CO₂ emissions, direct material flows, although Canaset et al. (2003) and Seppalaet. (2001) have discovered contradictory findings; and biodiversity loss (Asafu-Adjaye, 2003). The paper is formatted as follows: The "Review of literature" Section examines the pertinent literature. The "Methodology" Section describes the empirical foundation. "Results and discussion" describes the data and discusses the empirical findings, whilst "Conclusions" provides concluding remarks.

Literature review

CO₂ emissions are a leading indicator of environmental degradation since they induce climate change and global warming (Apergis & Payne, 2009; Du et al., 2012; Lean & Smyth, 2010; Shahbaz et al., 2013, 2016; Tiwari et al., 2013). Higher atmospheric CO₂ levels produce greenhouse effects and higher ambient temperatures (Bacastow et al, 1985; Hofmann et al., 2009; IPCC, 2015; Liu et al., 2016). By 2100, atmospheric CO₂ will quadruple and air temperature will climb 1.5–5 °C if fossil fuels are burned (Baes et al., 1977; Kraaijenbrink et al., 2017; Mahlman, 1997). Carbon dioxide makes up three-quarters of global greenhouse gas (GHG) emissions (Huaman & Jun, 2014; IPCC, 2015). Many studies find mixed evidence linking economic expansion and environmental damage. Some find that the link between CO₂ emissions and economic growth is negative (Ajmi et al., 2015; Azomahou et al., 2006; Baek & Pride, 2014; Dogan & Aslan, 2017; Roca, 2001; Salahuddin, 2016) or initially positive but eventually negative (Riti et al., 2017; Shahbaz et al., 2014, 2016). Other studies

find a favourable correlation (Ahmad & Du, 2017; Bakhsh et al., 2017; Chaabouni et al., 2016; Ma et al., 2016; Nasir & Rehman, 2011; Ozturk & Acaravci, 2013; Saidi & Mbarek, 2016). Recent research using the autoregressive distributed lag (ARDL) model and a nonlinear version of it found a positive long-term relationship between economic growth and CO₂ emissions (Ahmad et al., 2018; Akalpler & Hove, 2019; Chen et al., 2019a, 2019b; Cosmas et al., 2019; Dong et al., 2018; Gill et al., 2018; Khan et al., 2019; Riti et al., 2017; Toumi & Toumi, 2019). Those publications may have mixed outcomes due to sample period, country-specific factors, model specifications, econometric methodologies, and pollution indicators. The environmental Kuznets curve (EKC), similar to the inverted U-shaped curve used by Kuznets (1955) to model income inequality and income levels, is the most frequent framework for studying the relationship between CO₂ emissions and economic growth in single nations or groups of countries. Grossman and Krueger (1991, 1995), Stern and Common (2001), Dinda (2004), Friedl and Getzner (2003), Dinda and Coondoo (2006), and Managi and Jena (2006) were early investigations (2008). Some studies support the existence of an EKC (Ahmad, 2016; Ang, 2007; He & Richard, 2010; Iwata et al., 2010; Katz, 2015; Lau et al., 2014; López-Menéndez, 2014); others do not (Jia et al., 2009; Liu et al., 2007a, 2007b; Magazzino, 2014a, 2014b, 2015; Pao et al., 2012; Riti & Shu, 2016); some report an N-shaped relationship (Kijima et al., 2010). Mikaylov et al. (2018) use Johansen, ARDL, DOLS, FMOLS, and CCR cointegration methods to test for an EKC in Azerbaijan and find that economic growth has a positive and statistically significant long-term effect on emissions, disproving the EKC hypothesis. Ru et al. (2018) use a recently developed methodology based on long-term growth rates (Stern et al., 2017) to model the income–emission relationship for four sectors (power, industry, residential, and transportation) and three types of pollutants (SO₂, CO₂, and BC (black carbon)). The analysis uses data for various countries from the global emission inventory developed at Peking University and finds that the results are both sector and policy-specific. Barassi and Spagnolo (2012) estimate a VAR-GARCH (vector autoregression—generalized autoregressive conditional heteroskedastic) model and find mean and volatility spillovers between per capita economic growth and carbon dioxide emissions in Canada, France, Italy, Japan, UK (United Kingdom), and USA (1870–2005). Panel studies supporting the EKC hypothesis include Martínez-Zarzoso and Bengochea-Morancho (2004) for 22 OECD countries; Farhani et al. (2014) for 10 Middle East and North African (MENA) countries; Gao and Zhang (2014) for 14 sub-Saharan African countries; Kasman and Duman (2015) for 15 countries: Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Iceland, Latvia, Lithuania, FYR of Macedonia, Malta,

Poland, Romania, Slovak Republic, Slovenia, and Kim (2019) for newly industrialised Asian countries; Apergis and Payne (2009) for six Central American countries; Anastacio (2017) for Canada, the and Mexico. Onafowora and Owoye (2014) for Brazil, China, Egypt, Japan, Mexico, Nigeria, South Korea, and South Africa (only Japan and South Korea found an EKC); Mallick and Tandi (2015) for Bangladesh, India, Nepal, Pakistan, and Sri Lanka; Zoundi (2017) for 25 countries; and Wang (2012) for 98 countries found no EKC. These inconsistent results reflect panel heterogeneity. Single-country studies suggest an EKC: Ozturk and Oz (2016) for Turkey; Latifa et al. (2014) for Algeria; Khan et al. (2019) and Shahbaz et al. (2012) for Pakistan; Sothan (2017) for Cambodia; Yazdi and Mastorakis (2014) for Iran; Saboori et al. (2016) for Malaysia; Can and Gozgor (2017) for France; Saboori (2012) for Malaysia; Khalid (2014) for Mongolia; Shahbaz (2015) for Portugal. Saleh and Abedi (2014) and Saboori and Soleymani (2011) for Iran; Ghosh et al. (2014) and Amin et al. (2012) for Bangladesh; Friedl and Getzner (2002) for Austria; Boopen and Vinesh (2011) for Mauritius; Alkhatlan et al. (2012) for Saudi Arabia; Saboori et al. (2012) for Indonesia; and Dogan and Turkekul (2016) for the USA found no EKC. Pollution indicators, model specifications, estimate methods, and sample period can explain differences in results. Few CO₂ emission studies use fractional integration/cointegration. Galeotti et al. (2009) test 24 OECD nations and find no support for the EKC theory. Barassi et al., 2018 use this approach to analyse stochastic convergence of relative per capita CO₂ emissions. They found little evidence in the OECD countries but higher evidence in the BRICS (Brazil, Russia, India, China, and South Africa). The former cannot be explained to structural discontinuities. Gil-Alana et al. (2017) employ a long-memory technique with nonlinear trends and structural breaks to BRICS and G7 data to study CO₂ emissions' stochastic behaviour (USA, UK, France, Italy, Germany, Japan and Canada). Except in Germany, the US, and the UK, CO₂ emission spikes have persistent effects. Though it exclusively considers China, this paper goes further than theirs by linking GDP growth and CO₂ emissions. China's large economy and considerable CO₂ emissions have attracted other studies. Some examine economies of scale, population, energy structure, economic activity, and energy intensity (Xie et al., 2018; Xu, 2014). (Jalil & Mahmud, 2009; Liu et al., 2007a, 2007b; Zhang et al., 2009) (2005). Peters et al. (2007) found using SDA (structural decomposition analysis) that China's CO₂ emissions from infrastructure construction, urbanisation, household consumption, and lifestyle have outpaced efficiency reductions. However, Li and Wei (2015) find that the impact of industrial structure on carbon dioxide emissions is gradually changing from positive to negative and that carbon intensity is the key

driver of CO₂ emission reduction in China. Zhang et al. (2015) use SDA to study China's pollutant variables and find that increasing emission efficiency and intensity reduces industrial pollution. In China, some studies find evidence for the EKC (Haisheng et al., 2005; Jalil & Mahmud, 2009; and Jalil & Feridun, 2011); others do not (Du et al., 2012; Wang et al., 2011a, 2011b); others find an inverted N-shaped relationship between CO₂ and GDP (Fang et al., 2019; Kang et al., 2016; Onafowora & Owoye, 2014) (Wang et al., 2019); and some report the existence of a N trajectory (Dinda et al., 2000; Friedl & Getener, 2003; Lipford & Yandle, 2010; Martinez-Zarzoso & Begonchea-Morancho, 2004; Onafowora & Owoye, 2014).

The findings of various studies on the shape of the Environmental Kuznets Curve (EKC) vary widely. Some studies (Neve and Hamaide, 2017; Pal and Mitra, 2017; Rehman and Rashid, 2017) found no EKC while a number of other studies (Tang and Tan, 2015; Xu and Lin, 2015; Balaguer and Cantavella, 2016; Ozatac et al., 2017) found it inverted U-shaped. The debate over the shape of the EKC still continues among the researchers.

Table 1. Annual Exponential Growth Rate

Period	CO ₂ Emissions	Industrial Value Added	GDP Per Capita
1990 to 2000	5.00	3.8	5.8
2000 to 2010	6.00	5.1	8.00
2010 to 2019	4.3	5.3	5.1

Source: Author's calculation

During the entire period of 30 years from 1990 to 2019, the period was pertained in three phases: phase I (1990 to 2000), phase II (2000 to 2010) and phase III (2010 to 2019). In phase I, CO₂ emissions grew at 5.00 %, industrial value added 3.8 %, and GDP per capita 5.8 %. In phase II, CO₂ emissions grew at 6.00 %, industrial value added 5.1 %, and GDP per capita only 8.00 %. In the last phase III, CO₂ emissions grew at 4.3 %, industrial value added 5.3 %, and GDP per capita 5.1 % (Table 1). Thus, it seems that a spur in the growth of GDP per capita is associated with reduction in CO₂ emissions between the three equal phases 1990-2000, 2000-2010 and 2010-2019. The primary objective of this paper is to examine the pattern of relationships of CO₂ emissions with GDP per capita (GDPPC) and industrial value added (INDVA) in the Indian context.

Data and methodology

This analysis employed 1990-2019, CO₂ emissions (Kt) as a metric of environmental degradation, GDP per capita at constant 2015 US\$, and industrial value added at constant

US\$. World Development Indicators on www.worldbank.com provided the data (2020). CO₂ emissions and GDP and industrial value added per capita are of particular interest. This article examines the long-term links between CO₂ emissions, GDP per capita, and industrial value added, as well as the dynamic adjustment of the first difference of the variables. It especially examines India's 1990–2019, CO₂ emissions rise. Time series econometric methods including Augmented Dickey-Fuller (ADF) unit root test for stationarity, Johansen co-integration test for long-run relationships, and vector error correction model (VECM) for long-run relationship validity are used. The first ADF test establishes the econometric methods utilised by determining the stationarity and order of integration of time series variables. If each variable is stationary or integrated of order zero (I(0) at level), we build a multiple regression model to analyse the variables' relationships. If each variable is integrated of order 1 (I(1)), we first use the Johansen trace and maximum eigenvalue tests to identify the number of co-integrated vectors, then estimate VECM and perform other model adequacy tests to confirm the long-run link between the variables. Finally, we test variable causality using VECM Granger causality. Co-integration between non-stationary variables indicates a long-term equilibrium relationship. Thus, these variables never separate over time. The vector error correction model VECM assesses the dynamic modifications of the first difference of variables, while the co-integration test examines long-term dynamic connections. The VECM only works if system variables are cointegrated. Grossman (1995) believed wealth growth degraded the environment. The argument supporting the falling component of the Environmental Kuznets Curve is that as affluence grows, demand for a healthier environment increases, triggering a better response from policymakers and regulators. Thus, as money rises, environmental degradation will first climb up to a certain level, then plummet and follow an inverted U-curve as the desire for a healthy environment rises. Environmental awareness and consumer demand drive greener industrial technologies. Local air quality measures including SO₂, SPM, CO, and NO_x show an inverted-U connection with income. Several studies (Grossman and Krueger, 1995; Selden and Song, 1994; Stern and Common, 2001; List and Gallet, 1999; Shukla and Parikh, 1992; Barbier, 1997; Brandoford et al., 2005; Matyas, 1998; Patel, 1995; Ansuategi, 1998; Jha, 1996; Horvath, 1997; Tucker, 1995; Roca, 2003) have confirmed this relationship. EKC is rarely seen for air contaminants with negligible health impact. Previous and contemporary research show that global pollutants like carbon dioxide emissions either monotonically rise or reduce with income. Spurious regression findings are conceivable if the environmental indicator and GDP per capita are moving (nonstationary). Year-specific time dummies reduce the issue. First-difference model

estimation may work. Only co-integrated variables are better. Few research have considered this issue (Galeotti et. al., 2006; Perman and Stern, 2003; Stern, 2000; Stern and Common, 2001). We investigated the likelihood of cointegration or long-term link between CO2 emissions, industrial value added, and GDP per capita due to some academics' worries.

Time series properties

Before using the right econometric techniques to look for relationships between the variables CO2, INDVA, and GDPPC in log form, we first look at the properties of each of the above time series.

Unit root test

The Augmented Dickey-Fuller (ADF) unit root test is the most common econometric model used to do a unit root test on a time series. The ADF test takes autocorrelation in error terms into account and uses the following model to test whether a time series variable, Y_t , is stationary:

$$Y_t = \beta_0 + \beta_1 + \phi_1 Y_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta Y_{t-1} + \varepsilon_t$$

where ϕ_1 is the auto-regression parameter, ε_t is the non-systematic component of the model that meets the characteristics of the white noise process.

The null hypothesis $H_0: \phi_1=1$, i.e. the series y_t contains a unit root or it is non-stationary I(1),

Alternative hypothesis $H_1: \phi_1 < 1$, i.e. the series y_t does not contain a unit root or it is stationary, I(0)

Johansen co-integration test and VECM

An $(N \times 1)$ vector of time series x_t is co-integrated if each series is integrated of order 1 (I(1)) and some linear combination $\beta'x_t$ is stationary (I(0)) for some non-zero vector β . Co-integrating vector β . Linear combination of non-stationary variables is co-integration. Integrate all variables in order. Researchers use Johansen test to determine co-integrated vectors and VECM to confirm the long-term link between variables. Co-integration indicates that if one variable rises, the other either rises also or falls after a while to maintain their long-term link. Co-integrated variables must return to their "equilibrium relation" following shock-induced re-adjustment. Johansen tests the rank of 0 equal to the number of co-integrating vectors β checks how many 0 eigenvalues are statistically significant. Three options:

1) $r = 0$ i.e. $\Pi=0$, each time series is non-stationary and they do not share any common trend, VAR in first differences can be used without loss of long term information.

(2) $0 < r < N$, r co-integration relationship exist

(3) $r = N$, all the time series are stationary and standard VAR in levels is appropriate.

To test for the number of co-integrating vectors, Johansen (1995) proposed a method based on the maximum likelihood estimate of matrix Π_0 and its eigenvalues. The rank of Π_0 is in general equal to the number of its nonzero eigenvalues. Two test statistics are used:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^N \text{Log}(1 + \lambda_i)$$

And

$$\lambda_{Max}(r) = -T \sum_{i=r+1}^N \text{Log}(1 + \lambda_{r+1})$$

The λ_{trace} : H_0 : rank $\Pi_0 \leq r$ against the alternative H_A : rank $\Pi_0 > r$

Whereas λ_{max} : H_0 : rank $\Pi_0 \leq r$ against the alternative H_A : rank $\Pi_0 = r+1$

The expression $\beta' x_t$ can be restated in a way that allows easier interpretation: from the error correction formulation $e_t = \beta' x_t$ we can normalize the co-integrating relation by setting one co-efficient to 1. The cointegrating relationship is then written in a similar way as standard regression model: $x_{it} = \beta' x_{jt}$.

When estimating the number of co-integrating relationships, eigenvalues of Π_0 are estimated and ordered from the highest to the lowest. The highest eigenvalue corresponds to a co-integrating relationship that is correlated with the stationary component at most. In comparison with the Engle-Granger procedure the Johansen procedure allows for more co-integrating vectors and more complicated equilibrium relationships: Generally, the $I(0)$ equilibrium relationship can be written as

$$Z_t = u + \gamma_t + \beta_1 y_{1t} + \beta_2 y_{2t} + \beta_n y_{nt} \dots \dots \dots 2$$

The term $\mu + \gamma t$ represents the deterministic component of the co-integrating relationship meaning that the linear combination does not have to be necessarily zero, but either constant or even with linear trend. Therefore, the VECM representation in general is

$$x_t = u + \rho + \alpha \beta x_{t-1} + \sum_{i=1}^p \pi_i \Delta x_{t-1} + \varepsilon_t \dots \dots \dots 3$$

Where α is the matrix of adjustment coefficients of order $N \times r$. Each adjustment coefficient must have appropriate signs for adjustment to take place for maintaining long-run relationships in case of any deviation from it. The product $\alpha \beta'$ is a $N \times N$ matrix. If we define $\Pi_0 = \alpha \beta'$, then equation (3) can be written as equation (4) given below.

$$x_t = u + \rho + \pi_0 x_{t-1} + \sum_{i=1}^p \pi_i \Delta x_{t-1} + \varepsilon_t \dots \dots \dots 4$$

We expect that the three variables CO_2 , $GDPPPC$ and $LINDAVA$ in log forms are co-integrated i.e. there is a longrun relationship among the three variables as follows:

$$CO_2 = \beta_0 + \beta_1 GDPPPC + \beta_2 LINDVA_t + \epsilon_t \quad (5)$$

Where $LCO2_t$ = Natural log of Carbon Dioxide Emissions in year t

$LINDVA_t$ = Natural log of Industrial Value Added in year t

$LGDPCC_t$ = Natural log of Gross Domestic Product Per Capita in year t

ϵ_t = Error in year t. β_0 , β_1 , and β_2 are parameters to be estimated. The expected signs of the parameters are as follows: $\beta_1 > 0$, and β_2

If β_1 has expected sign and is statistically significant, with no change in $LGDPCC$, there will be a positive relationship between LCO_2 and $LINDVA$. Similarly, if β_2 has expected sign and is statistically significant, with no change in $LINDVA$, there will be a negative relationship between LCO_2 and $LGDPCC$.

Results and discussion

Stationarity test

Since, the variables are time series, running directly a multiple regression involving these variables may produce a spurious regression if these time series are not all stationary. Hence, checking for their stationarity by using appropriate test, among other things, is pre-requisite for validating or invalidating the estimated regression.

Table 2. Augmented Dickey-Fuller Unit-Root Test

Variable	PP				ADF				
	At level	prob	1 st difference	prob	At level	prob	1 st difference	prob	Decision
LCO2	-0.498	0.877	-4.9255	0.000*	-0.5227	0.8727	-4.772	0.000*	I(1)
LINDVA	-0.193	0.928	-2.8647	0.062*	-1.3084	0.6113	-4.9767	0.000*	I(1)
LGDPCC	2.8293	1	-5.161	0.000*	2.0754	0.9998	-2.8752	0.061*	I(1)

*Indicates that t-value is significant at 10%. Source: Author's calculation using E-Views 10.0 software

In order to search for the possibility of a long-run relationship among these variables (LCO_2 , $LINDVA$ and $LGDPCC$), and nature of it first of all we conducted the Augmented Dickey-Fuller and Puller (PP) unit root test on each of the above time series variable. None of them was found to be stationary at level but each of them was found to be stationary at first differencing. That is each of them was found to be $I(1)$ series. Under this situation the chance of estimated multiple regression between the variables being spurious become high even if coefficient of determination is very high and all coefficients are highly significant (Table 2).

Table 3. AIC and SC for Optimum Lag Length in Unrestricted VAR

Lag	LogL	LR	FPE	AIC	SC	HQ
0	81.43441	NA	4.81E-07	-6.03342	-5.88825	-5.99161
1	202.2595	204.4732*	8.91E-11	-14.6353	-14.05468*	-14.4681
2	213.6612	16.66405	7.66e-11*	-14.82009*	-13.8039	-14.52747*
3	218.7425	6.253967	1.13E-10	-14.5187	-13.067	-14.1006
4	222.606	3.863452	1.98E-10	-14.1235	-12.2364	-13.5801

In view of the above results, the possibility of co-integration among the variables has to be explored. For this, the lag-length criteria were used on vector autoregressive (VAR) system including all the three series as endogenous variables for choosing optimum lag length before applying the Johansen co-integration test. Based on Akaike Information Criterion 2 lags were selected and applied for the Johansen co-integration test (Table 3).

Johansen cointegration test Both the trace test and max-eigenvalue test unanimously indicates 1 co-integrating equation at 5 percent level of significance in Johansen co-integration test with the assumption of linear deterministic trend in the series with optimum lags 2 as selected by optimum lag selection criteria (Table 4). Since the three endogenous variables (LCO2, LINDVA, and LGDPP) are co-integrated with one cointegrating vector and with each series being I(1), the appropriate model is vector error correction model (VECM). Hence, the VEC model is estimated with one co-integrating equation and 2 lags (one less than 2 lags selected by optimum lag selection criteria) in difference terms.

Table 4. Johansen Co-integration Test

Unrestricted Co-integration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.7229	42.90771	29.79707	0.0009
At most 1	0.32243	10.81919	15.49471	0.2229
At most 2	0.042591	1.088121	3.841466	0.2969
Trace test indicates 1 co-integrating eqn(s) at the 0.05 level				
Unrestricted Co-integration Rank Test (Max-Eigen)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.722945	32.08852	21.13162	0.001
At most 1	0.32243	9.731072	14.2646	0.2302
At most 2	0.042591	1.088121	3.841466	0.2969

Max-eigenvalue test indicates 1 co-integrating eqn(s) at the 0.05 level

Table 5 Long-run Vector Error Correction Estimates

Cointegrating Eq:	CointEq1
LCO2(-1)	1
LGDP(-1)	-2.4363
	-1.27666
	[-1.90834]
LIVA(-1)	1.155073
	-0.90591
	[1.27505]
C	-27.7814
CointEq1	-0.041534
	-0.05395
	[0.76983]

Table 5 the estimate shows that CO2 significantly affected the economic growth of India in the long run. The coefficient of GDP is 2.43 and respective t-statistics is -1.90. It reveals that CO2 sector impact the economy of India at 5 percent level of significance. In the long-run, 1 percent increase in CO2 lead to 2.43 percent of economic growth in India. In addition to agriculture, long-run results show that industrial value added also significantly does not promote the economic growth of India. Error correction term shows the speed of adjustment towards the long run equilibrium. Value of error correction term is -0.041, it shows that 4.15 percent point adjustment would take place each year towards the long run equilibrium. It is statistically significant at 1 percent level of significance. Negative sign indicates the convergence towards the long run equilibrium. In the table 6 model summary is given, it shows the value of r-square is 0.4527, which reveals that all the explanatory variable taken in the model are explaining 45.27 percent.

Table 6 Model summary of long run regression

R-squared	0.4527	Mean dependent var	0.051
Adjusted R-squared	-0.194	S.D. dependent var	0.026
S.E. of regression	0.029	Akaike info criterion	-3.922

Sum squared resid	0.009	Schwarz criterion	-3.24
Log likelihood	63.037	Hannan-Quinn criter.	-3.73
F-statistic	0.699	Durbin-Watson stat	2.09
Prob(F-statistic)	0.732		

To check the model stability and robustness, some diagnostic test such as Breusch- Godfrey test for serial correlation, Breusch-Pagan- Godfrey test for hetroscedasticity, Jarque-Bera test for normality, Cusum test and Cusum of square test for model stability have been analyzed. From the table 7 results (F-statistics=0.068, p=0.79 and R-squared=0.152, p=0.696) reveals that the null hypothesis of Breusch-Godfrey serial correlation LM test “there is no serial correlation” has been accepted. It implies model is free from serial correlation. Similarly the estimates (F=1.69, p=0.18) of Breusch- Pagan-Godfrey test has failed to reject the null hypothesis “model is homoskedastic”. It implies that model is free from the hetroskedasticity and error term has constant variance that lead to the unbiased model. As far as normality of the model is concerned, error term should be normally distributed. Jarque-Bera test of normality has been examined for the null hypothesis that “errors are normally distributed”. From the figure 1, it is reveals that test estimates (Jarque- Bera =0.30, p=0.85) accept the null hypothesis. It implies that errors are normally distributed. The normal distribution of error is very important especially when we want to sure about interpretation of estimated model. Cusum and Cusum of square test is one most useful test to examine the model stability. Cusum test is based on the cumulative sum of the equation error in the regression. Graphically the cumulative sum of error together with critical lines of 5 percent is presented in the figure 1. The model parameters are considered stable because the line of whole sum of recursive errors is within the two critical lines which is indicated by red color in the figure 1. It implies that model is sufficiently stable. Similarly, from the figure 2, Cusum of square test also shows that model is adequately stable and results are reliable.

Table 8 Diagnostic test

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.068039	Prob. F(1,12)	0.7986
Obs*R-squared	0.152225	Prob. Chi Square(1)	0.6964

Table 9 Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.699272	Prob. F(15,11)	0.1894
Obs*R-squared	18.86058	Prob. Chi-Square(15)	0.2201
Scaled explained SS	3.842964	Prob. Chi-Square(15)	0.9982

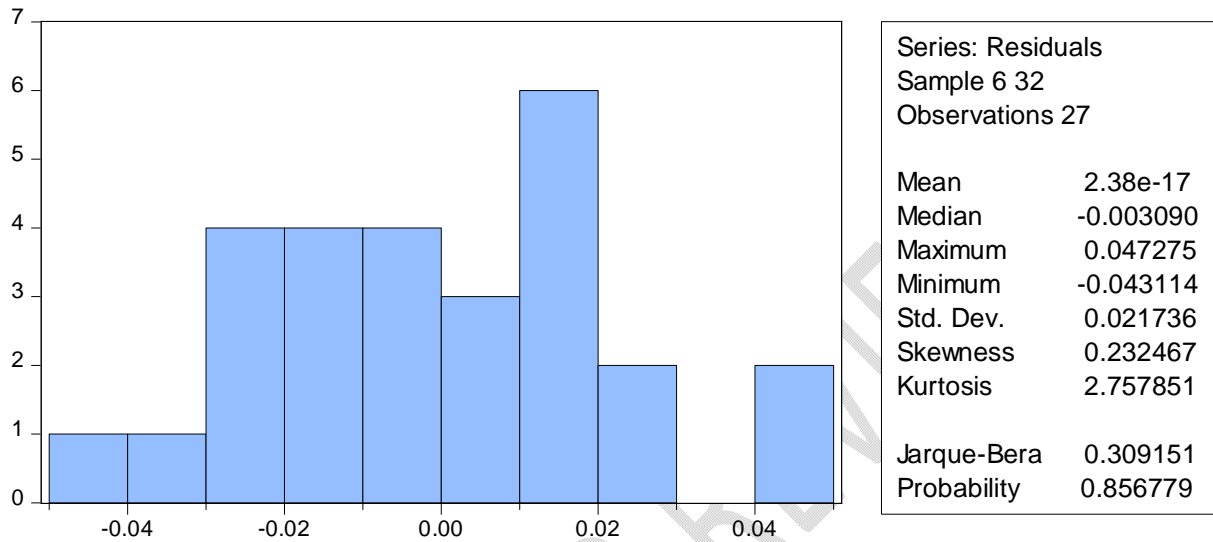


Figure 1 Cumulative sum of error together with critical lines of 5 percent

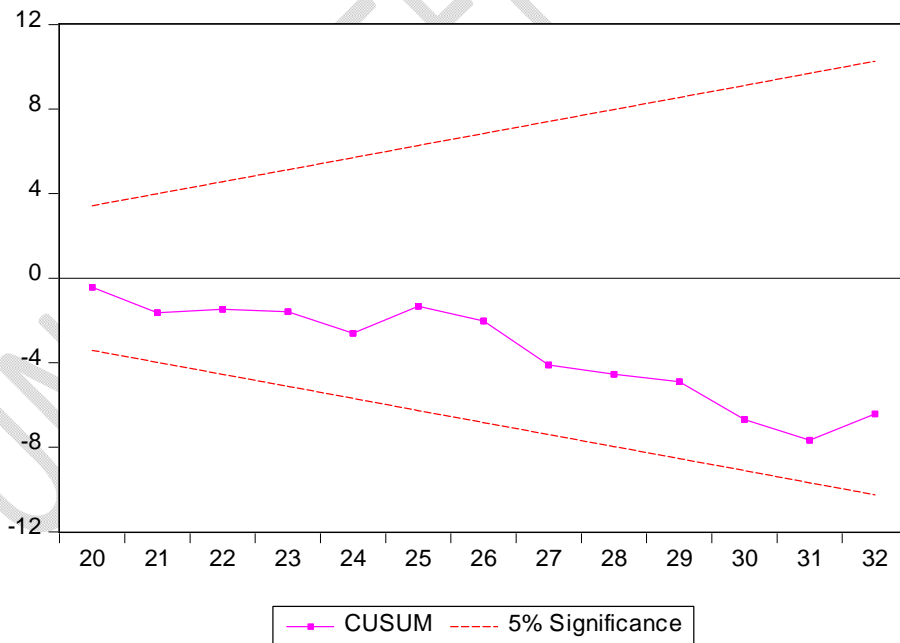
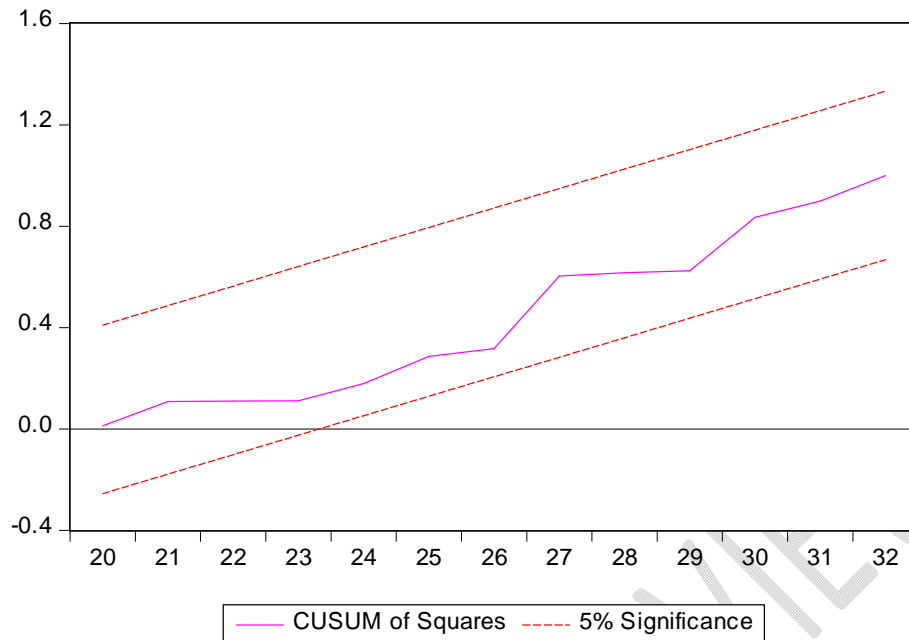


Figure 2 Cusum of square test



Conclusion

This study investigated the impact of economic development on quality of environment in India. Growth in GDP per capita and CO₂ emissions are used as a measure of economic development and environmental degradation respectively. Econometric analysis applying Johansen co-integration test and vector error correction model (VECM) indicates that there is a long-run relationship among CO₂ emissions, GDP per capita and industrial value added. Industrial value added remaining constant, CO₂ emissions increase with rise in the level of GDP per capita. Growth in GDP per capita is found to be negatively related with CO₂ emissions in India. But with no change in GDP per capita, CO₂ emissions rise with rise in industrial value added. In other words, if we control for industrial value added, the relationship between CO₂ emission and GDP per capita is a monotonous downward sloping curve instead of inverted U-shaped curve as hypothesized by Environment Kuznet's Curve. But, if we control for GDP per capita, the relationship between CO₂ emissions and industrial value added is upward sloping curve. Irrespective of its level, rise in per capita income has a positive impact on environmental quality provided that there is no growth in industrial value added. Only the downward sloping part of Environment Kuznet's Curve is found to exist with no change in industrial value added. This finding has an important implication for India in the long-run. In the long-run, as it generally happens in a country, when growth in industrial value added will become stagnant any further economic development via growth in other sectors will improve the quality of environment in India. However, increased demand for environmental regulation may not be a quasi-automatic response with economic growth.

Structural shift away from manufacturing may also explain the falling part of EKC relationship. Economic growth and liberalization should be thought of as a solution for environmental problems. However, it would be more optimal for India to follow higher economic growth path along with policy responses influencing other socio-economic factors that would induce improvement in environmental quality. Policy measures involving inducements, incentives along with measures to spur economic growth will ensure sustainable development path for India.

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