International Journal of Development and Sustainability
ISSN: 2186-8662 – www.isdsnet.com/ijds
Volume 8 Number 9 (2019): Pages 558-573
ISDS Article ID: IJDS19021104

Economic development and CO2 emissions in India

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Abstract

This study investigates the impact of economic development on quality of environment in India. GDP per capita and CO_2 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 CO_2 emissions, GDP per capita and industrial value added. Industrial value added remaining constant, CO_2 emissions increase with rise in the level of GDP per capita. GDP per capita is found to be negatively related with CO_2 emissions in India. But with no change in GDP per capital, CO_2 emissions rise with rise in industrial value added. In other words, if we control for industrial value added, the relationship between CO_2 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 CO_2 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 growth 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 will improve the quality of environment in India.

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

Cite this article as: Alam, F. (2019), "Economic development and CO2 emissions in India", *International Journal of Development and Sustainability*, Vol. 8 No. 9, pp. 558-573.

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1. Introduction

The environmental Kuznets curve (EKC) hypothesizes that at a low level of development, indicators of environmental degradation is high and as level of development rises indicators of environmental degradation fall. In other words, it predicts inverted U-shaped relationships between indicators of various types of environmental degradation and economic development. The EKC is named after Kuznets (1955) who hypothesized that income inequality first rises with rise of economic development and then falls as economic development exceeds a certain threshold level.

The EKC concept gained momentum in the early 1990s with Grossman and Krueger's (1991) path-breaking study of the potential impacts of NAFTA and it was popularized through the 1992 World Bank Development Report (World Bank, 1992).

If the EKC hypothesis were true, then rather than being a threat to the environment, as claimed by the environmental movement and associated scientists (Meadows et. al., 1972) in the past, economic growth would be the automatic means to eventual environmental improvement.

This change in thinking was already underway in the emerging idea of sustainable economic development promoted by the World Commission on Environment and Development (1987) in 'Our Common Future'. The possibility of achieving sustainability without a major deviation from business as usual was obviously an enticing prospect for many––letting humankinds ''have our cake and eat it too'' (Rees, 1990).

The EKC is essentially an empirical phenomenon, but most of the EKC literature is econometrically weak. In particular, very little attention has been paid to the statistical properties of the data used––such as serial dependence or stochastic trends in time-series and little consideration has been given to the issues of model adequacy such as the possibility of omitted variables bias.

However, one of the main purposes of applying econometrics is to test which apparent relationships are valid and which are spurious. When we do apply diagnostic statistics and specification tests and use appropriate techniques, we find that the EKC does not exist. Instead, we get a more realistic view of the effect of economic growth and technological changes on quality of environmental. It seems that emissions of most pollutants and flows of waste rise monotonically with income, though the ''elasticity of environmental degradation with respect to income" is less than one and is not a simple function of income alone (Perman and Stern, 2003).

Environmental damages, in the long run, are caused by the economic growth. At the centre of this relationship lies the observed inverted-U shaped relationship between output growth and the level of pollution. This relationship is known as the Environment Kuznet's Curve (EKC). Moreover, stricter enforcement of environmentally beneficial government policies promotes environmental awareness and stricter ecological regulations can be put in place. As a result, the economy shifts towards less polluting sectors and adoption of more environmental friendly technologies (Panayotou, 1993).

Better quality of the environment is also considered to be correlated with higher economic growth. There are a number of theoretical explanations for this relationship. Environmental quality is considered by some as normal good and hence its income elasticity is more than zero. That is, as level of income rises people place more value to environmental quality leading to more concern about the environment (Beckerman, 1992; World Bank, 1992).

As income grows, the possibility of using better and less pollution-intensive capital and technology also increases (Grossman and Krueger, 1995). Moreover, as economic prosperity increases in a country the share of industrial output in total output declines and share of service sector rises. These sectoral changes are also in favour of the environment (Jänicke et. al., 1997). But at a lower level of income, as share of agriculture and industrial sector increases the overall environmental quality goes down. Besides, the low income under-developed countries are more likely to attract more pollution intensive industries from high income developed countries popularly known as "pollution haven hypotheses".

In the early stage of development as an agrarian economy is gradually transformed to industrial one, environmental degradation is likely to increase. But at a more advanced stage when the economy further transfers from industrial to more service based economy, a fall in environmental quality becomes likelier.

In the long-run, there are three main drivers that cause a change in scale and sources of environmental degradation. These three main drivers are changes in economic structure, scale of economy and technology. If there is no change in economic structure and technology, increase in the scale of economy will lead to increase in environmental degradation. This is generally known as scale effect. At higher levels of development, structural changes in favour of service sectors, coupled with increased environmental awareness, enforcement of environmental regulations, better technology and higher environmental expenditures, result in leveling off and gradual decline in environmental degradation (Panayotou, 1993). These direct or immediate causes are themselves determined by factors such as environmental regulations, awareness and education.

For some aspects of the environment, turning point does not exist. Examples include CO_2 emissions, direct material flows but Canas et. al. (2003) and Seppala et. al. (2001) have found contrary evidence; and biodiversity loss (Asafu-Adjaye, 2003).

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
1980-14	5.68%	6.54%	5.48%
1980-96	6.77%	5.89%	1.99%
1997-14	5.60%	7.48%	9.85%

Source: Author's calculation

During the entire period of 35 years from 1980 to 2014 CO_2 emissions grew at 5.68 %, industrial value added 6.54 %, and GDP per capita 5.48 %. During the first half of the period from year 1980 to 1996 CO_2 emissions grew at 6.77 %, industrial value added 5.89 %, and GDP per capita only 1.99 %. But during the second half of the period from year 1997 to 2014 CO_2 emissions grew at 5.60 %, industrial value added 7.48

%, and GDP per capita 9.85 % (Table 1). Thus, it seems that a spur in the growth of GDP per capita, is associated with reduction in CO_2 emissions between the two equal sub-periods 1980-96 and 1997-2014.

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.

The rest of the paper is organized as follows. In section 2, we describe the variables included, data sources for these variables and methods of data analysis adopted. In section 3 we present the the empirical results of estimated models and discuss the relationship among the above three variables in India. Finally, we conclude the paper in section 4.

2. Data and methodology

The data used in this study consist of CO_2 emissions (in Kt.) as a measure of environmental degradation, GDP per capita at constant 2010 US$, and industrial value added at constant US $, for the period 1980-2014. The data were compiled from World Development Indicators published by the World Bank on its website www.worldbank.com (2017).

We specifically want to examine the nature of relationships of CO_2 emissions with GDP per capita and industrial value added per capita.

This paper investigates the long-run linkages between CO_2 emissions, GDP per capita and industrial value added and the dynamic adjustment of the first difference of the variables, and specifically analyzes the impact of growth in GDP per capita and industrial value added on CO_2 emissions in India during 1980 to 2014.

The time series econometric techniques such as, Augmented Dickey-Fuller (ADF) unit root test for stationarity, Johansen co-integration test for detecting long-run relationships and vector error correction model (VECM) for checking the validity of long-run relationship is applied.

First ADF test is conducted to know the stationarity property and order of integration of the time series variables since it determines the types of econometric techniques to be used subsequently. After testing for the stationarity of each variable and order of integration, if each variable is found to be stationary or integrated of order zero i.e. I(0) at level then we estimate a multiple regression model to further investigate the nature of relationships among the variables. If, instead, each variable is found to be integrated of order 1 i.e. I(1) we first apply the Johansen trace and maximum eigenvalue tests for finding number of co-integrated vectors and then estimate VECM and conduct various model adequacy tests for confirming the long-run relationship among the co-integrated variables. Finally, we conduct VECM Granger causality test for examining the causality among the variables.

The presence of co-integration among some variables means that even though they are non-stationary, there is a long-run equilibrium relationship among them. In other words, these variables never drift apart in the long run. While co-integration test measures the dynamic linkages among different variables in the long-run, the vector error correction model VECM is also utilized to measure the dynamic adjustments of the first difference of variables. It should be noted that the VECM can only be used if the variables in the system are co-integrated.

Grossman (1995) proposed that income growth had negative impact on the quality of the environment. The hypothesis supporting the falling part of the Environmental Kuznets Curve is that as income grows demand for better quality of environment also increases triggered by a better response from policy makers and regulators. Thus as income rises environmental degradation will first increase up to a certain level of income and then starts falling and follows an inverted U-curve path as the need for a beneficial environment increase. The greater environmental awareness and greener consumer demand leads to adoption of more environmental friendly production technologies.

The local air quality indicators such as sulphur dioxide (SO_2), suspended particulate matters (SPM), carbon monoxide (CO) and nitrous oxides (NO_x), etc. generally reveal the inverted-U relationship 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 et al., 1998; Patel et al., 1995; Ansuategi et al., 1998; Jha, 1996; Horvath, 1997; Tucker, 1995; Roca, 2003) have confirmed this relationship. Generally, the literature does not find the existence of EKC for air pollutants that have little direct impact on health. Both previous and recent studies find that the global pollutants such as carbon dioxide emissions either monotonically rise or fall as income grows.

If the environmental indicator and GDP per capita are both trending over time (in technical terms: are non-stationary), then spurious regression results are possible. Year-specific time dummies mitigate, but do not solve the problem. Estimating the model in first differences might work as a solution. Co-integration is superior, but only if variables are truly co-integrated. Very few studies have taken this potential problem seriously (Galeotti et. al., 2006; Perman and Stern, 2003; Stern, 2000; Stern and Common, 2001).

In view of the above concerns raised by some researchers, we have attempted to explore the possibility of co-integration or long-run relationship among the three variables i.e. CO_2 emissions, industrial value added and GDP per capita.

2.1. Time series properties

Before searching for relationships among the variables CO_2, INDVA and GDPPC in log form by applying appropriate econometric technique, we first investigate the time series properties of each of the above time series.

2.1.1. Unit root test

The most popular econometric model that is used for conducting unit root test on a time series is the Augmented Dickey-Fuller (ADF) unit root test. The ADF test accounts for autocorrelation in error terms and uses the following model for testing stationarity in a time series variable y_t as follows:

$$y_t = \beta_0 + \beta_1 t + \phi_1 y_{t-1} + \sum_{i=1}^{P-1} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

where ϕ_1 is the autoregression parameter, ε_t is the non-systematic component of the model that meets the characteristics of the white noise process. The null hypothesis is H_0: ϕ_1 =1, i.e. the series y_t contains a unit root or it is non-stationary, I(1), alternative hypothesis is H_1: $|\phi_1|$ < 1, i.e. the series y_t does not contain a unit root or it is stationary, I(0).

2.2. Johansen cointegration test and VECM

An (N×1) vector of time series x_t is said to be co-integrated if each of the series taken individually is integrated of order 1 i.e. I(1) while some linear combination $\beta' x_t$ is stationary, or I(0), for some non-zero (N×1) vector β. The β is referred as co-integrating vector. Co-integration corresponds to linear combination of non-stationary variables. All variables must be integrated of the same order.

Johansen test is the most prominent among the researchers for finding number of co-integrated vectors among the variables and the VECM for checking and confirming the long-run relationship among these variables.

Co-integration between any two variables means if one variable moves up, the second either does the same or the first decreases after some time to keep their long-term relationship stable. Co-integrated variables cannot wander off in a long-term and must arrive to its “equilibrium relation” after re-adjustment in the variables due to a shock.

The Johansen procedure tests the rank of Π_0 which equals to the number of co-integrating vectors β. Technically, it tests how many eigenvalues of Π_0 are statistically significant. Three possibilities arise:

(1) r = 0 i.e. Π=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-integrating relationships 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:

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

and

$$\lambda_{max}(r+1) = -T\log(1-\lambda_{r+1})$$

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

Whereas λ_{max} : H_0 : *rank* $\Pi_0 \leqslant r$ 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 co-integrating 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

$$z_t = \mu + \gamma\, t + \beta_1 y_{1t} + \beta_2 y_{2t} + \ldots \beta_N y_{Nt} \quad (2)$$

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

$$x_t = \mu + \gamma t + \alpha \beta' x_{t-1} + \sum_{i=1}^{P} \prod_i \Delta x_{t-i} + \varepsilon_t \quad (3)$$

Where α is the matrix of adjustment coefficients of order N×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 αβ' is a N×N matrix. If we define $\Pi_0 = \alpha\beta'$, then equation (3) can be written as equation (4) given below.

$$x_t = \mu + \gamma t + \prod_0 x_{t-1} + \sum_{i=1}^{P} \prod_i \Delta x_{t-i} + \varepsilon_t \quad (4)$$

We expect that the three variables CO2, INDVA and GDPPC in log forms are co-integrated i.e. there is a long-run relationship among the three variables as follows:

$$LCO2_t = \beta_0 + \beta_1 LINDVA_t + \beta_2 LGDPPC_t + u_t \quad (5)$$

Where

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

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

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

u_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 $\beta_2 < 0$

If β_1 has expected sign and is statistically significant, with no change in LGDPPC, there will be a positive relationship between LCO2 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 LCO2 and LGDPPC.

3. Results and discussion

3.1. 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

Variables	Null Hypotheses	ADF test-statistic	Test critical values at 5%	Prob.
LCO2	The series has a unit root	-0.53760	-2.95113	0.87140
LINDVA	The series has a unit root	0.89302	-2.95402	0.99410
LGDPPC	The series has a unit root	1.43247	-3.63941	0.99870
Augmented Dickey-Fuller Unit-Root Test				
ΔLCO2	The series has a unit root	-5.62391*	-2.95402	0.0000
ΔLINDVA	The series has a unit root	-4.20256*	-2.95402	0.0024
ΔLGDPPC	The series has a unit root	-5.16519*	-3.64634	0.0002

**Indicates that t-value is significant at 1%.*
Source: Author's calculation using EViews 8.0 software

In order to search for the possibility of a long-run relationship among these variables (LCO2, LINDVA and LGDPPC), and nature of it first of all we conducted the Augmented Dickey-Fuller 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 length	0	1	2	3	4	5
Akaike AIC	-2.4259	-11.6687	-11.5495	-11.4109	-11.7247*	-11.6070
Schwarz SC	-2.2858	-11.1082*	-10.5686	-10.0097	-9.9032	-9.36515

Source: Author's calculation using EViews 8.0 software

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 4 lags were selected and applied for the Johansen co-integration test (Table 3).

3.2. Johansen contegration 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 4 as selected by optimum lag selection criteria (Table 4).

Since the three endogenous variables (LCO2, LINDVA, and LGDPP) are co-integrated with one co-integrating 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 3 lags (one less than 4 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	5% Critical Value	Prob.**
None *	0.6364	43.0194	29.7971	0.0009
At most 1	0.3426	12.6713	15.4947	0.1274
At most 2	0.0030	0.0894	3.8415	0.7650
Unrestricted Co-integration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5% Critical Value	Prob.**
None *	0.6364	30.3482	21.1316	0.0019
At most 1	0.3426	12.5819	14.2646	0.0907
At most 2	0.0030	0.0894	3.8415	0.7650

Source: Author's calculation using EViews 8.0 software

Subsequently the VECM) was estimated with one co-integrating equation and 3 lags as suggested by the Johansen co-integration test. VECM is an extension of vector auto-regressive (VAR) model with built-in error correction mechanism in it for maintaining long-run relationship among the co-integrated variables. The results of the estimated VECM are given in the table above (Table 5).

The above estimated VECM was checked for model adequacy using various tests such as tests for the presence of autocorrelation, hetroschadasticity, and normality of error terms.

The VECM residual Portmanteau test for autocorrelations under null hypothesis of no residual autocorrelations up to lag 12 was not rejected at even 10 percent level of significance (Table 6). Similarly, VECM Jarque-Bera residual normality test with null hypothesis that residuals are multivariate normal is not rejected at even 10 percent level of significance (Table 7). Finally, VECM residual heteroskedasticity tests with no cross terms (only levels and squares) does not reject the null hypothesis that residuals are not heteroskedastic at even 10 percent level of significance (Table 8). Hence, the estimated VEC model passes all tests of model adequacy.

Table 5. Vector Error Correction Estimates

Cointegrating Eq:	CointEq1		
LCO2(-1)	1.000000		
LINDVA(-1)	-1.496155		
	(0.07586)		
	[-19.7235]		
LGDPPC(-1)	0.662364		
	(0.08417)		
	[7.86977]		
C	21.19848		
Error Correction:	D(LCO2)	D(LINDVA)	D(LGDPPC)
CointEq1	0.124530	-0.222109*	-1.004088*
	(0.10594)	(0.08315)	(0.23137)
	[1.17549]	[-2.67135]	[-4.33970]
D(LCO2(-1))	-0.164854	0.380014	1.250000
	(0.30683)	(0.24081)	(0.67012)
	[-0.53729]	[1.57807]	[1.86535]
D(LCO2(-2))	-0.152639	0.274975	1.447735
	(0.23038)	(0.18081)	(0.50316)
	[-0.66254]	[1.52076]	[2.87727]
D(LCO2(-3))	0.206940	0.386699	1.119402
	(0.24808)	(0.19470)	(0.54181)
	[0.83417]	[1.98610]	[2.06604]
D(LINDVA(-1))	0.196810	-0.006042	0.034137
	(0.34562)	(0.27126)	(0.75485)
	[0.56944]	[-0.02227]	[0.04522]
D(LINDVA(-2))	0.378385	-0.49626	-1.842951
	(0.31152)	(0.24449)	(0.68037)
	[1.21464]	[-2.02975]	[-2.70876]
D(LINDVA(-3))	0.040376	-0.821855	-2.438141
	(0.33467)	(0.26266)	(0.73092)
	[0.12065]	[-3.12896]	[-3.33571]
D(LGDPPC(-1))	-0.000926	0.087856	-0.010123
	(0.09990)	(0.07840)	(0.21818)
	[-0.00927]	[1.12054]	[-0.04640]
D(LGDPPC(-2))	0.107412	0.134128	0.504864
	(0.09590)	(0.07526)	(0.20944)
	[1.12007]	[1.78209]	[2.41052]
D(LGDPPC(-3))	-0.084747	0.117451	0.422918
	(0.09505)	(0.07460)	(0.20758)
	[-0.89163]	[1.57448]	[2.03733]

C	0.023955	0.068574	0.054595
	(0.02775)	(0.02178)	(0.06060)
	[0.86334]	[3.14888]	[0.90090]
R-squared	0.419294	0.508044	0.640973
Adj. R-squared	0.128941	0.262066	0.461459
Sum sq. resids	0.015964	0.009834	0.076150
S.E. equation	0.028253	0.022174	0.061705
F-statistic	1.444085	2.065403	3.570609

Values in (….) are standard errors and in […] are the corresponding t-values
*Shows that the adjustment coefficients are significant at 1 %.
Source: Author's calculation using EViews 8.0 software.

Table 6. VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h					
Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	2.348918	NA*	2.427215	NA*	NA*
2	7.401170	NA*	7.827898	NA*	NA*
3	13.33611	NA*	14.39873	NA*	NA*
4	17.53019	0.2882	19.21415	0.2042	15
5	25.21600	0.3941	28.37800	0.2444	24
6	32.09924	0.5118	36.91322	0.2928	33
7	36.06302	0.7282	42.03310	0.4695	42
8	44.78299	0.7176	53.78611	0.3681	51
9	48.08378	0.8660	58.43722	0.5330	60
10	54.65167	0.8962	68.13268	0.5069	69
11	59.49704	0.9410	75.64300	0.5545	78
12	62.65217	0.9773	80.79085	0.6670	87

**The test is valid only for lags larger than the VAR lag order.*
df is degrees of freedom for (approximate) chi-square distribution.
Source: Author's calculation using EViews 8.0 software.

Table 7. VEC Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)				
Null Hypothesis: residuals are multivariate normal				
Component	Skewness	Chi-sq	df	Prob.
1	0.212826	0.234023	1	0.6286
2	-0.624282	2.013597	1	0.1559
3	0.055240	0.015766	1	0.9001
Joint		2.263385	3	0.5196
Component	Kurtosis	Chi-sq	df	Prob.
1	2.506457	0.314631	1	0.5749
2	2.406147	0.455521	1	0.4997

3	2.330589	0.578811	1	0.4468
Joint		1.348963	3	0.7175
Component	Jarque-Bera	df	Prob.	
1	0.548653	2	0.7601	
2	2.469118	2	0.2910	
3	0.594577	2	0.7428	
Joint	3.612348	6	0.7290	

Source: Author's calculation using EViews 8.0 software

Table 8. VEC Residual Heteroskedasticity Tests: No Cross Terms

Joint test:					
Chi-sq	df	Prob.			
117.2882	120	0.5530			
Individual components:					
Dependent	R-squared	F(20,10)	Prob.	Chi-sq(20)	Prob.
res1*res1	0.717262	1.268419	0.3597	22.23511	0.3279
res2*res2	0.507723	0.515689	0.9004	15.73942	0.7327
res3*res3	0.367991	0.291128	0.9909	11.40773	0.9350
res2*res1	0.503313	0.506671	0.9061	15.60271	0.7409
res3*res1	0.430662	0.378213	0.9692	13.35053	0.8618
res3*res2	0.381551	0.308474	0.9879	11.82808	0.9219

Sources: Author's calculation using EViews 8.0 software

Moreover all the three adjustment coefficients have expected signs but only two of them are statistically significant and hence paves way for extracting the long-run relationship among the three variables from the estimated VECM and explaining it.

In the system of VEC model with one co-integrating equation, the first equation is of particular interest. The first equation of the estimated VEC model was checked for residual serial correlation, normality and heteroskedasticity. The null hypotheses of no serial correlation, no normality and homoskedasticity of the residuals were not rejected at even 5 % level of significance. Thus, the equation passed all the major criteria for further analysis and interpretation. Moreover, In the VEC system, the signs of all the three adjustment coefficients were found to be as expected and also two of them statistically significant which brings us to the conclusion that the three variables are actually co-integrated and a long-run relationship exists among log value of CO_2 emissions, GDP per capita and industrial value added.

3.3. Estimates of the cointegrating vector

The long-run equilibrium relationship is presented below in equation (6).

$$LCO2 = -21.19848 + 1.494155*LINDVA - 0.662364*LGDPPC \quad (6)$$

s.e (0.07586) (0.08417)

t-value [-19.7235] [7.86977]

The above long-run equilibrium relationship indicates that with no change in GDP per capita, an increase in industrial value added causes an increase in CO_2 emissions. But with no change in industrial value added, growth in GDP per capita causes a fall in CO_2 emissions.

4. Conclusion

This study investigated the impact of economic development on quality of environment in India. Growth in GDP per capita and CO_2 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 CO_2 emissions, GDP per capita and industrial value added. Industrial value added remaining constant, CO_2 emissions increase with rise in the level of GDP per capita. Growth in GDP per capita is found to be negatively related with CO_2 emissions in India. But with no change in GDP per capital, CO_2 emissions rise with rise in industrial value added. In other words, if we control for industrial value added, the relationship between CO_2 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 CO_2 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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