An Econometric Analysis of Economic Development and CO_2 Emissions in India

Abstract

Purpose: The purpose of this article is to investigate the impact of economic development on the environment. Using time series data from 1991 to 2019, GDP per capita and CO2 emissions are utilised as indicators of economic development and environmental degradation, respectively.

Design/methodology/approach; PP and ADF unit root tests verify variable stationarity. Econometric study using Johansen cointegration test and vector error correction model (VECM) and residual stability model.

Findings; study revealed that long-run association among Carbon dioxide emissions, gross domestic product per capita, and industrial Value added. Carbon dioxide emissions increased with the rised in the Gross domestic product per capita. GDP per capita was outcomes to be unfavorably related to Carbon dioxide emissions in India.

Research limitations/implications; This study was suggest that environmental degradation can be reduced at the cost of economic development. Energy-efficient technologies should be encouraged to enhance the domestic product with the help of the industrial sector by improving environmentally friendly technologies from advanced economies. This study suggests the need for environmental policies to reduce emissions during periods of economic growth.

Originality/value; This paper used new econometric methods to study the relationship between economic development and environmental degradation in India year 1991 to 2019.

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

Introduction

According to the environmental Kuznets curve (EKC), the amount of environmental degradation that occurs is greatest at low development levels and diminishes as the level of development increases. It forecasts correlations in the form of an upside-down U between indices of environmental deterioration and levels of economic development. Kuznets (1955) proposed the idea that income disparity increases with economic development until it reaches a certain point, at which point it begins to decrease. This idea inspired the creation of the EKC. The research that (**Grossman and Krueger 1991**) on NAFTA's effects and the World Bank Development Report that was published in 1992 helped to popularise the EKC concept in the early 1990s (World Bank, 1992). If the EKC hypothesis is right, contrary to the beliefs of the environmental movement and scientists working in related fields, economic growth would automatically result in improvements to the environment **(Meadows et al., 1972).** In 1987, the World Commission on Environment and Development published "Our Common Future," which marked the beginning of a shift toward more sustainable economic development. The concept of "having our cake and eating it too" by achieving sustainability without compromising commercial interests was appealing to many people **(Rees, 1990).** Despite the statistical nature of most EKC research, the majority of it is unreliable from an econometric point of view. The statistical aspects of the data, such as serial dependency or stochastic patterns in time series, as well as model adequacy issues, such as bias from omitted variables, have not been taken into account. Nevertheless, econometrics assists in distinguishing between true and false relationships. The EKC can be eradicated through the utilisation of diagnostic statistics, specification tests, and appropriate methods. Instead, an assessment that is more grounded in reality of the effects of economic development and technological progress on environmental quality is provided. Despite the fact that the "elasticity of environmental deterioration with respect to money" is less than one and that it is not a straightforward function of income alone, the majority of pollutant and waste flows increase in a linear fashion with increasing wealth **(Perman and Stern, 2003**). Damage to the environment on a long-term basis is caused by economic growth. The rate of output growth and the amount of pollution are related in a U-shaped connection that is inverted. The Kuznets Environment Curve is a representation of this connection (EKC). Environmental awareness can be raised and more stringent ecological limitations can be implemented with the help of stronger enforcement of environmentally beneficial government programmes. As a result, the economy shifted towards more environmentally friendly businesses and technologies **(Panayotou, 1993)**. The quality of the environment may contribute to increased economic growth. This connection can be explained by a few different concepts. Since the quality of the environment is a typical good, its elasticity with respect to income is greater than zero. Concern for the environment is therefore proportional to financial means (**Beckerman, 1992; World Bank, 1992**). The accumulation of wealth paves the way for the development of capital and technologies that are more effective and produce less waste **(Grossman and Krueger, 1995**). When the economy of a country gets better, the production of the manufacturing sector goes down while the output of the service sector goes up. The environment benefits from reforms in various sectors (**Janicke et al., 1997).** Agriculture and industry both flourish when incomes are lower, which leads to a degradation of the surrounding ecosystem. According to the "pollution haven hypothesis," low-income developing nations draw pollution-intensive businesses from high-income industrialised nations. These businesses are located in high-income industrialised nations. It is anticipated that early industrialization will have a greater influence on the environment. It is possible that environmental quality will deteriorate as the economy shifts from being based on manufacturing to services. There are three primary factors that contribute to the degradation of the ecosystem over time. The primary factors are size, economic structure, and technological advancement. If the structure of the economy and the technologies used do not change, economic expansion will be harmful to the environment. The influence of scale At greater levels of growth, structural changes favouring service sectors, improved environmental consciousness, enforcement of environmental rules, improved technology, and higher environmental expenditures level out and diminish environmental impact (**Panayotou, 1993).** Direct causes are determined by environmental regulations, environmental awareness, and environmental education. Some ecological components never turn. Emissions of carbon dioxide, direct material flows, the loss of biodiversity, and contradictory findings from **(Canaset et al. 2003) and Seppalaet (2001**) respectively.

Formatting is shown. This section reviews relevant literature. Methodology describes empirical base. "Results and discussion" and "Conclusions" discuss the data and empirical findings.

Literature review

The major indicators of environmental damage are climate change and global warming, both of which are caused by emissions of carbon dioxide (**Tiwari et al., 2013).** CO2 causes a rise in both the greenhouse effect and the average temperature **(Liu et al., 2016).** Seventy-five percent of the world's greenhouse gas (GHG) emissions are carbon dioxide (**Huaman and Jun, 2014).** The data that links economic growth with environmental damage is inconsistent, according to a number of studies. Some researchers have found that CO2 emissions and economic growth either have a negative correlation (**Ajmi et al., 2015; Salahuddin, 2016)** or initially had a positive correlation but now have a negative correlation (**Shahbaz et al., 2014).** Others see a favourable association between the two **(Ahmad and Du, 2017).** Recent studies that utilised the autoregressive distributed lag (ARDL) model and a nonlinear version indicated a positive long-term correlation between economic growth and CO2 emissions. This association was shown to be beneficial. **(Ahmad et al., 2018).** There is a possibility that the conclusions of those papers are inconsistent because of factors such as the length of the sample, the unique characteristics of the country, the model assumptions, the econometric methods, and the pollution indicators. “The environmental Kuznets curve (EKC), which is very similar to the inverted U-shaped curve that Kuznets (1955) used to describe income inequality and income levels, is the most common framework for evaluating CO2 emissions and economic growth in individual nations or groups of nations". "This curve was named after Kuznets, who also developed the curve that was used to describe income levels. Some studies suggest the existence of an EKC" **(Ahmad, 2016**). other studies suggest that there is no such thing The EKC hypothesis is invalidated by the finding that economic expansion has a long-term influence on emissions in Azerbaijan that is both positive and statistically significant (**Ru et al. 2018)** implement a fresh approach to calculating the long-term growth rate. "To model the income–emission connection for four industries (power, industry, residential, and transportation) and three pollutants (SO2, CO2, and B.C.) **(Stern et al., 2017),** the researchers used a mathematical equation (black carbon)". This study examines the worldwide emission inventory maintained by Peking University for a number of different countries in order to arrive at industry- and policy-specific findings. (**Barassi and Spagnolo 2012)** use "an estimate of a VAR-GARCH model, which stands for vector autoregression—generalized autoregressive conditional heteroskedastic, to discover mean and volatility spillovers between per capita economic growth and carbon dioxide emissions in Canada, France, Italy, Japan, the United Kingdom, and the United States (1870–2005)". "Panel studies that provide support for the EKC hypothesis include (Martnez and -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 (Slovenia, and Kim 2019) (Onafowora and Owoye 2014) Bangladesh, India, Nepal, Pakistan, and Sri Lanka; (Mallick and Tandi 2015) Bangladesh, China, Egypt, Japan, Mexico, Nigeria, South Korea, and South Africa; (Zoundi 2017) 25 nations; and (Wang 2012) 98 countries detected no EKC". The heterogeneity of the panel was the root source of these inconsistencies. Single-country studies point to the existence of an EKC. These studies include: (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 It's possible that the results can be explained by pollution indicators, model parameters, estimation approaches, or even sampling time. Only a small number of studies on CO2 emissions make use of fractional integration or cointegration. The EKC theory did not receive support from any of the 24 OECD countries (Galeotti et al. 2009). Utilizing this approach, an analysis of the stochastic convergence of relative per capita CO2 emissions is carried out

(Barassi et al., 2018). The BRICS nations possessed a greater quantity of evidence than the OECD (Brazil, Russia, India, China, and South Africa). Structural discontinuities cannot explain it. (Gil-Alana et al. 2017) examine the stochastic behaviour of CO2 emissions by using data from the BRICS and G7 countries, as well as a long-memory approach that incorporates nonlinear trends and structural breaks (USA, UK, France, Italy, Germany, Japan, and Canada). The rate of increase in CO2 emissions is lowest in Germany, followed by the United States and the United Kingdom. This paper, in contrast to theirs, which only considers China, links growth in GDP to increases in CO2 emissions. Several other studies have investigated China's massive economy as well as its CO2 emissions. Some researchers focus on factors such as population size, energy structure, economic activity, and energy intensity (Xie et al., 2018; Xu, 2014). According to the results of a structural decomposition analysis (SDA), China's CO2 emissions from infrastructure construction, urbanisation, household consumption, and lifestyle surpassed reductions in efficiency (Peters et al. 2007). On the other hand, (Li and Wei 2015) show that the structure of industry is gradually shifting from being positive to being negative, and that the reduction of carbon intensity is the primary driver of CO2 emission reduction in China. According to the findings of SDA's research on China's pollutant factors, increasing emission efficiency and intensity brings about a reduction in industrial pollution (Zhang et al. 2015). Some studies in China locate the EKC (Haisheng et al., 2005; Jalil and Mahmud, 2009; and Jalil and Feridun, 2011); other studies in China do not (Du et al., 2012; Wang et al., 2011a, 2011b); some studies locate an inverted N-shaped relationship between CO2 and GDP (Wang et al., 2019); and some studies report the existence of a N trajectory (Dinda et al., 2000; Friedl and Getener, 2003; Lipford and Yandle, 2010; Martinez-Zarzoso and Begonchea-Morancho, 2004; Onafowora and Owoye, 2014).

The Environmental Kuznets Curve has been found to take a variety of forms according to the studies that have been conducted (EKC). Some research reported no EKC, while others found it inverted U-shaped (Tang and Tan, 2015; Xu and Lin, 2015). The EKC form has been debated by researchers.

Table 1. Annual Exponential Growth Rate

Period	CO2 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

The 30-year period from 1990 to 2019 was divided into three phases: phase I, from 1990 to 2000, phase II, from 2000 to 2010, and phase III (2010 to 2019). Phase I CO2 emissions increased by 5.00%, industrial value added increased by 3.8%, and GDP per capita increased by 5.8%. In Phase II, industrial value added was 5.1%, GDP per capita was only 8.00%, and CO2 emissions increased by 6.00%. Phase III CO2 emissions increased by 4.3%, industrial value added increased by 5.3%, and GDP per capita increased by 5.1%. (Table 1). Thus, it would appear that a spike in GDP per capita growth is linked to a decline in CO2 emissions over the three equal time periods of 1990–2000, 2000–2010, and 2010–2019. This research main goal is to investigate how CO2 emissions relate to Gross domestic product per capita (GDPPC) and industrial value added (INDVA) in the context of India.

Methodology

This study used 1991–2019, Carbon dioxides emissions (Kt) as a estimats of environmental damage, Gross domestic product per capita in 2015 US dollars, and industrial Value added in 2015 US dollars as constants. The information came from World Development Indicators on www.worldbank.com (2020). There is a lot of interest in CO2 emissions, GDP, and industrial value added per person. This article looks at the long-term relationships between Carbon dioxides emissions, Gross domestic product per capita, and industrial Value added. It also looks at how the first difference between the variables changes over time. It looks at the rise in India's CO2 emissions from 1991 to 2019. Time series econometric methods are used, such as the Augmented Dickey-Fuller (ADF) unit root test for stationarity, the Johansen cointegration test for long-run relationships, and the vector error correction model (VECM) for the validity of long-run relationships. The first ADF test finds out which econometric methods were used by figuring out whether time series variables are stationary and in what order they are integrated. If each variable is stationary or integrated of order zero (I,(0) at level), we build a multiple regression model to figure out how the variables are related. If each variable is integrated of order 1 (I(1)), we first use the Johansen trace and maximum eigenvalue tests to find out how many co-integrated vectors there are. After that, we estimate VECM and do other model adequacy tests to make sure that the variables are linked in the long run. Cointegration between variables that don't stay the same over time shows that they are in long-term equilibrium. So, these things don't change over time. The vector error correction model (VECM) looks at how the first difference between two variables changes over time, while the cointegration test looks at how long-term dynamic connections change over time. The VECM only works if the variables in the system are all tied together. Grossman (1995) thought that more money hurt the environment. The falling part of the

Environmental Kuznets Curve is supported by the idea that as wealth grows, people want a healthier environment more, which makes policymakers and regulators act better. So, as money goes up, the damage to the environment will first go up to a certain level, then go down in an inverted U shape as the desire for a healthy environment goes up. Greener industrial technologies are driven by consumer demand and awareness of the environment. SO2, SPM, CO, and NOx are some of the local air quality measurements that show a U-shaped relationship with income. Several studies (Grossman and Krueger, 1995; Selden and Song, 1994; Stern and Common, 2001; List and Gallet, 1999; Jha, 1996; Ansari, et. al., 2022; Ansari, et. al., 2022) have confirmed this link. EKC is rarely used for air pollutants that don't pose much of a health risk. Research from the past and the present shows that carbon dioxide emissions and other global pollutants either always go up or always go down with income. If the environmental indicator and GDP per capita are moving, this could lead to false regression results (nonstationary). Problems are less of a problem when time dummies include the year. The first-difference model may be a good way to estimate. Only variables that are both co-integrated are better. Few studies have looked into this (Galeotti et. al., 2006; Perman and Stern, 2003; Stern, 2000; Stern and Common, 2001). Some academics were worried about a long-term link between CO2 emissions, industrial Value added, and GDP per capita..

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.

$LCO_2 = \beta_0 + \beta_1 GDPPPC + \beta_2 \text{LINDV}A_t$……………………………………………1

Where LCO2t = Natural log of Carbon Dioxide Emissions in year t

LINDVAt= Natural log of Industrial Value Added in year t

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

ut = Error in year t. β0 β1, , and β2 are parameters to be estimated. The expected signs of the parameters are as follows: β1 >0, and β2

Unit root test

When doing a unit root test on a time series, the econometric model known as the Augmented Dickey-Fuller (ADF) unit root test is by far the most frequent model to apply. The autocorrelation in error terms is taken into consideration by the ADF test, which then applies the following model to determine whether or not a time series variable, Yt, is stationary:

$$Y_t = \beta_0 + \beta_1 + \emptyset_1 Y_{t-1} + \sum_{i=1}^{p-1} \gamma \Delta Y_{t-1} + \varepsilon_t$$

where$\emptyset_1$ 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 H0: $\emptyset_1$=1, i.e. the series yt contains a unit root or it is non-stationary I(1),

Alternative hypothesis H1: $\emptyset_1$< 1, i.e. the series yt does not contain a unit root or it is stationary, I(0)

Johansen co-integration test and VECM

Johansen (1995) proposed a method that is based on the maximum likelihood estimate of matrix 0 and its eigenvalues in order to test for the number of co-integrating vectors. This method was developed in order to test for the number of co-integrating vectors. In most circumstances, the rank of 0 is equal to the number of its eigenvalues that are not zero. There are two types of test statistics used:

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

And

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

trace: H0: rank 0r in comparison to the alternative HA: rank Π0>r

On the other hand, max: H0: rank 0r in contrast to the alternative H A: rank Π0=r+1

Results and discussion

Stationarity test

Running directly a multiple regression containing these variables could result in a misleading regression if the time series being analysed are not all stationary. This is due to the fact that the variables in question are time series. Checking the stationarity of the data by employing the proper test is, therefore, one of the pre-requisites for validating or invalidating the calculated regression. Other pre-requisites include:.

Table 2. Augmented Dickey-Fuller and PPUnit-Root Test

PP					ADF					
Variable	**At level**	**prob**	**1st difference**	**prob**	**At level**	**prob**	**Istdifference**	**prob**	**Decision**
LCO2	-0.498	0.877	-4.9255	0.000*	-0.5227	0.8727	-4.772	0.000*	**I(I)**
LINDVA	-0.193	0.928	-2.8647	0.062*	-1.3084	0.6113	--4.9767	0.000*	**I(I)**

LGDPPC	2.8293	**1**	-5.161	0.000*	2.0754	0.9998	-2.8752	0.061*	**I(I)**

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

The Augmented Dickey-Fuller and Puller (P.P) unit root test was performed on each of the above time series variables in order to search for the possibility of a long-run relationship among these variables (LCO2, LINDVA, and LGDPPC), as well as the nature of it. This was done in order to search for the nature of the relationship. It was discovered that none of them were stationary when levelled, yet it was discovered that all of them were stationary when first differencing. That is to say, it was discovered that each of them was an I(1) series. Even though the coefficient of determination is very high and all of the coefficients are highly significant, the likelihood that the estimated multiple regression between the variables contains false relationships is substantial when the scenario is as described above (Table 2).

Table 3. AIC and S.C. 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 considering the results presented above, it is necessary to investigate whether or not there is cointegration among the variables. Before conducting the Johansen cointegration test, the lag-length criteria were utilised on a vector autoregressive (VAR) system that included all three series as endogenous variables in order to choose the optimal lag length. This was done in order to accomplish this goal. Two lags were chosen and used for the Johansen cointegration test based on the Akaike Information Criterion (Table 3).

Johansen contegration test Both the trace test and the max-eigenvalue test revealed unequivocally that there is one co-integration equation at the 5 percent level of significance in the Johansen cointegration test with the assumption of a linear deterministic trend in the series using optimum lags 2 as selected by the optimum lag selection criteria (Table 4). As a result of the fact that the three endogenous variables (LCO2, LINDVA, and LGDPP) are co-integrated with a single cointegrating vector and that each series is I(1), the vector error correction model is the one that should be used (VECM).

Table 4. Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of C.E. (s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical**	**Prob.****

			Value	
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 Cointegration Rank Test (Max-Eigen)				
HypothesizedNo. of CE(s)	**Eigenvalue**	**Max-EigenStatistic**	**0.05Critical 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

CointegratingEq:	**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]

According to Table 5, the calculation demonstrates that CO_2 has a considerable impact on the overall economic growth of India over time. The GDP coefficient comes in at 2.43, and the corresponding t-statistics come in at -1.90. It has been determined that the CO_2 industry has an impact on the economy of India that is five percent as significant. An rise of one percent in CO_2 levels leads to a decrease of 2.43 percentage points in economic growth in India over the long term. In addition to the field of agriculture, results over the long term suggest that the field of industrial value added significantly does not promote the expansion of the Indian economy. The error correction term indicates how quickly the system is adjusting to reach its long-term equilibrium. The value of the error correction term is -0.041, which indicates that an adjustment of 4.15 percentage points would be made annually in order to reach the long run equilibrium. At the one percent threshold of statistical significance, it is significantly different from zero. A negative sign signifies that we are moving closer and closer to the equilibrium state over the long run. The model's summary is presented in table 6, where it is shown that the value of r-square is 0.4527. This indicates that all of the explanatory variables included in the model account for 45.27 percent of the total variance.

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		

Some diagnostic tests, such as the Breusch- Godfrey test for serial correlation, the Breusch-Pagan- Godfrey test for hetroscedasticity, the Jarque-Bera test for normality, the Cusum test and the Cusum of square test for model stability have been analysed. This has been done in order to check the model's stability and robustness. The null hypothesis of the Breusch-Godfrey serial correlation L.M. test, which states that "there is no serial correlation," has been accepted as a consequence of the findings presented in table 7, which show that F-statistics equaled 0.068, p equaled 0.79, and R-squared equaled 0.152, p equaled 0.696. It suggests that the model does not exhibit any serial correlation. In a similar vein, the estimations of the Breusch- Pagan-Godfrey test (F = 1.69, p = 0.18) did not successfully reject the null hypothesis that "model is homoskedastic." It denotes that the model does not contain any hetroskedasticity and that the error term has a constant variance, both of which contribute to the unbiased model. The error term ought to have a normal distribution, taking into account the normality requirements of the model. It has been determined by the use of the Jarque-Bera test of normality that the alternative hypothesis, "errors are not normally distributed," is false. The test estimates (Jarque-Bera=0.30, p=0.85) are consistent with the assumption that the null hypothesis is true, as shown in figure 1. It gives the impression that errors are spread normally. The normal distribution of error is very significant, particularly in situations in which we need to be certain about the interpretation of an estimated model. One of the most helpful tests for determining the stability of the model is the Cusum and Cusum of square test. The cumulative total of the equation error in the regression serves as the foundation for the cusum test. The cumulative accumulation of error, together with crucial lines of 5 percent, is illustrated graphically in figure 1, which may be seen here. Because the line of full sum of recursive mistakes is located inside the two crucial lines, as shown by the colour red in figure 1, the model parameters are judged to be stable. It suggests that the model has an adequate amount of stability. In a similar, the Cusum of squares test, which can be shown in figure 2, demonstrates that the model is sufficiently stable and that the findings may be trusted.

Table 7 Diagnostic test

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

Table 8 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

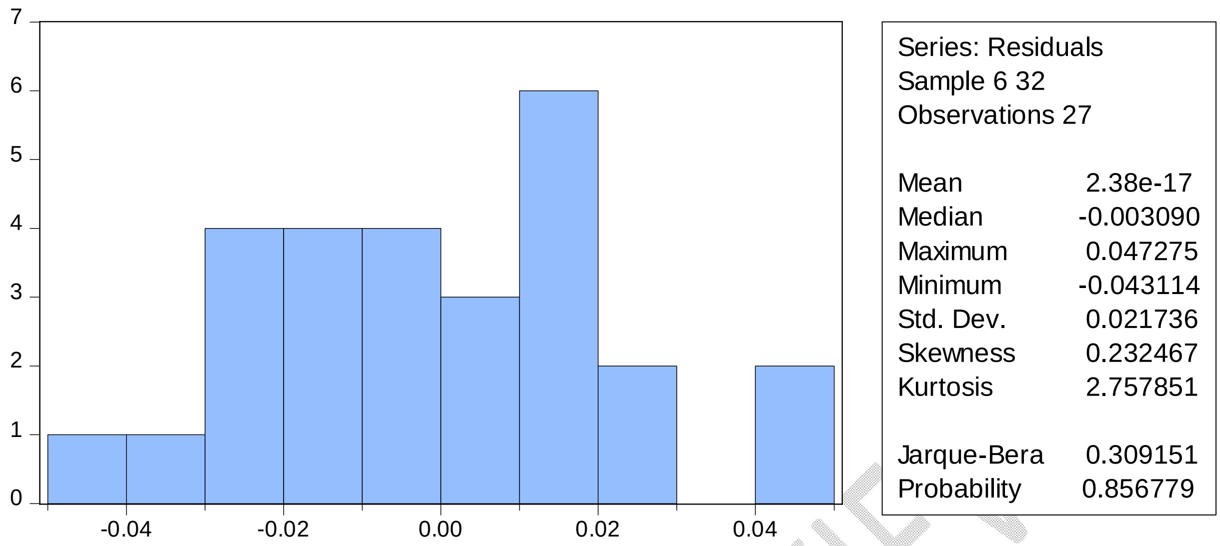
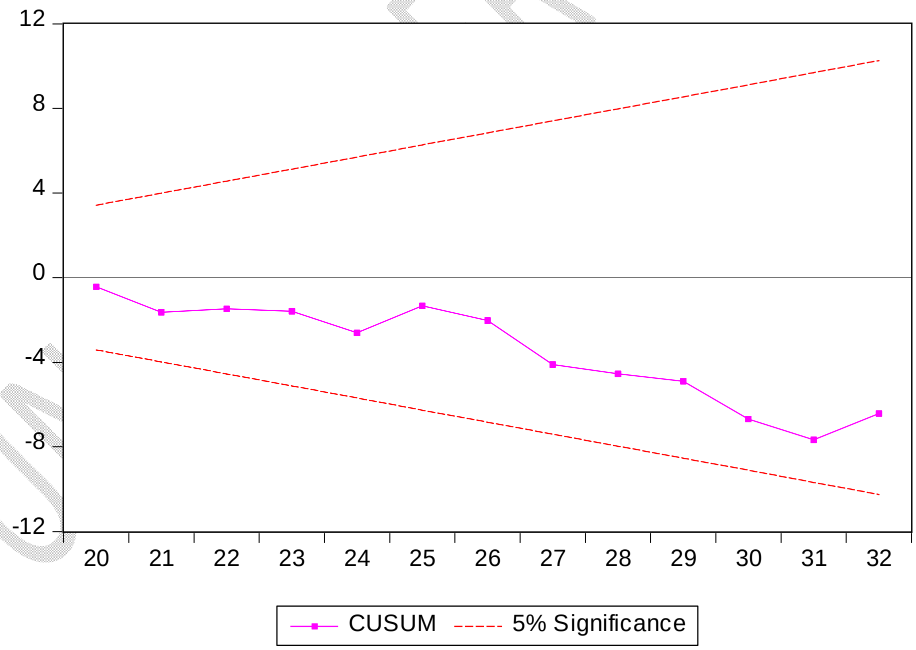
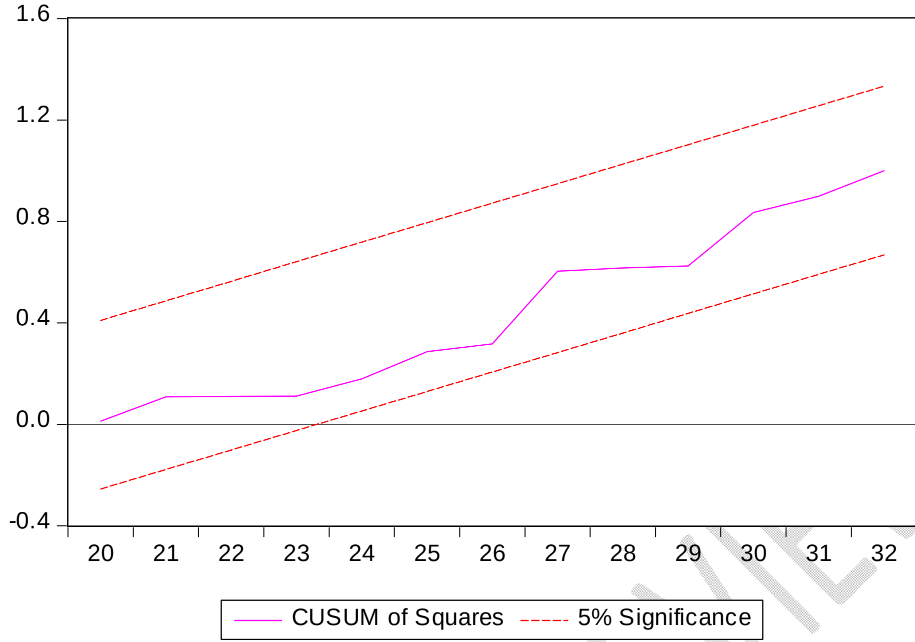


Figure 1 Cumulative sum of error together with critical lines of 5 percent



(A)



(B)

Figure 2Cusum of square test

Conclusion

The significance of India's rapid economic growth to the country's overall environmental quality was the subject of this study. Both the growth in gross domestic product per capita and the growth in carbon dioxide emissions are employed as measures of the progression of economic development and of the degradation of the environment, respectively. Using the Johansen cointegration test and the vector error correction model (VECM), econometric study shows that there is a long-run link between carbon dioxides emissions, gross domestic product per capita, and industrial Value added. There is no change in the value contributed to industry, but there has been an increase in the amount of carbon dioxide released into the atmosphere. Researchers in India have discovered an inverse relationship between increases in GDP per capita and the country's total CO2 emissions. However, assuming that GDP per capita stays the same, CO2 emissions will increase along with the value generated by industry. In other words, if we adjust for industrial Value added, the relationship between CO2 emissions and GDP per capita is not an inverted U-shaped curve as suggested by

Environment Kuznet's Curve but rather a monotonically trending downwards curve instead of a U-shaped curve inverted. However, if we adjust for factors such as GDP per capita, we see that the relationship between CO2 emissions and the value contributed by industry follows an ascending curve. A gain in per capita income, irrespective of its amount, has a direct impact on environmental quality, provided that there is no growth in industrial value-added. The only component of Environment Kuznet's Curve that is discovered to exist without a change in industrial Value added is the part that slopes downward. This conclusion has significant long-term repercussions for India, which are vital to consider. In the long run, when growth in industrial value added would become stagnant as it typically does in a country, any additional economic development in India via growth in other sectors will increase the quality of the environment in India. This is because it is generally what happens in a country. On the other hand, an increase in the demand for environmental control could not be a response that is almost automatic to economic expansion. It is possible that the declining part of the EKC connection can also be explained by the structural move away from manufacturing. The promotion of economic expansion and liberalisation ought to be viewed as potential solutions to environmental issues. Nevertheless, it would be better for India to follow a path of faster economic growth together with policy responses that influence other socio-economic elements that would improve environmental quality. This would be the ideal course of action. A route toward sustainable development can be ensured for India through the use of policy measures such as inducements, incentives, and measures to encourage economic growth.

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