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The spillover effects of uncertainty and globalization on environmental quality in India: Evidence from combined cointegration test and augmented ARDL model

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Environmental quality and climate change have become hot topics among academics in all scientific fields in recent decades due to their impact on human health and economic development. Hence, this paper investigates the key factors of carbon dioxide emissions in India from 1970–2020 through the Bayer-Hanck test and Augmented ARDL framework on an augmented STIRPAT model, introducing uncertainty and globalization. We employ a set of unit-root tests and a combination of cointegration techniques (DOLS and FMOLS), which permit us to estimate the long-run and short-run relationships. Empirical findings confirmed that the series is I(1) series and there is the existence of a long-run relationship between our variables using three cointegration tests, meaning that the variables have the same behavior in the long run term. The findings revealed that India has an inverse U shape of the Environmental Kuznets curve (EKC) due to the positive association between GDP *per capita* and CO_2 emissions until reaching a threshold, after which the link becomes inverse due to the negative impact of GDP square on CO_2 emissions. Furthermore, the findings demonstrated a positive influence of uncertainty and a negative impact of globalization on long-term environmental degradation. Besides, energy consumption and population density are positively associated with CO_2 emissions in the long and short run. We advocate for policies that promote more trade openness by entering new markets and cooperating with new trading partners.

KEYWORDS

CO_2 emissions, economic Uncertainty, globalization, environmental quality, STIRPAT model

1 Introduction

All the members of the United Nations, including India, have adopted the 2030 agenda for sustainable development, which focuses on mutual understanding among the nations to carry out future objectives where human lives are improved alongside protecting the environment. Out of the seventeen sustainable development goals, such as eliminating poverty, erasing hunger, reducing inequality, Grow Affordable and Clean Energy, and improving Clean Water and Sanitation, the thirteenth goal focused on acting against climate change and combating its effects on the environment. India has a dual role to play in global climate politics. Besides being a developing country with low levels of *per capita* emissions (Parikh et al., 2009), India is also an emerging economy with rising emissions (Dubash, 2013), and its greenhouse gas and carbon dioxide emission contribute to global warming. The impact of climate change on agriculture and human health is severe and varies significantly across various regions of the country (Dash and Hunt, 2007). In addition, Tripathi et al. (2016) reveal the deepening negative effect of global warming on agricultural production poses a serious threat to food security.

The largest source of greenhouse emissions in India is the electricity and heat sector, followed by the agriculture, manufacturing, and construction sector. About 3.21% of global cumulative carbon dioxide is emitted by India (Ritchie and Roser, 2020). Besides, the government has framed various policies to improve environmental quality, worsening daily. Hence, there is not much achievement in this regard because there is a massive gap between the aim of the policies implemented and the current measures taken (Reich and Bowonder, 1992). Moreover, in recent years, India has been very open to the outside world, with a large increase in foreign trade and significant foreign direct investment inflows, which shows the Government's approach to globalization in all its aspects. Two adverse effects have characterized the literature on the relationship between globalization and the environment. First, globalization contributes to economic growth by increasing countries' foreign trade and investment flows. In an attempt to satisfy foreign direct investment (FDI), governments, especially in developing countries, may overlook the environment by overlooking non-environment-friendly means of production, which causes environmental degradation in the long run. Secondly, globalization has excellent benefits in distributing clean means of production and new technologies that would improve the environment. In other words, globalization is considered an ideal solution for spreading environmentally friendly technologies in developing countries, which still use traditional production methods that harm the environment. This automatically means improved environmental conditions in the long run for developing countries.

Furthermore, many researchers have attempted to identify the factors that upsurge environmental degradation. Mohapatra and Giri (2009) investigated the link between economic development and CO_2 emissions using the EKC (Environmental Kuznets Curve) hypothesis. Shahbaz et al. (2015) used annual data from 1970 to 2012 to test the link between globalization and carbon dioxide emissions in India. They discovered that a rapid increase in globalization and energy consumption has significantly escalated carbon dioxide emissions. According to the study, economic growth is inversely related to carbon dioxide emissions. Villanthenkodath and Mahalik (2020) used annual data covering 1980 to 2018 to study the association between technological innovations and environmental quality in India. Tourism development and structural change also have a pivotal role in environmental degradation; thus, Villanthenkodath et al. (2021) discovered that tourism degrades environmental quality in their study. According to current literature, the demand for environmental quality is low in countries such as India due to poverty, so less attention is paid to this issue (Jalan et al., 2009).

It is clear that in recent years, particularly following the 2008 financial crisis, the issue of economic uncertainty has become a sensitivetopic in any economic study, as many studies have emerged attempting to understand the impact of this uncertainty on various economic indicators. Moreover, as is well known, anything that affects the economy automatically impacts the climate and the environment. This has resulted in some recent studies attempting to investigate the impact of economic uncertainty on climate change (Ayad et al., 2023; Wang K. H. et al., 2020; Liu and Zhang, 2022 and Syed and Bouri, 2021). Economic policy uncertainty (EPU) is defined by Gulen and Ion (2016) as the inability of economic agents to predict the possible economic consequences, timing, and content of policy decisions. This situation causes these agents to take precautionary and preventive procedures to avoid future shocks related to any doubt or suspicion in economic activities. As a result of the previous crises that the global economy has faced (the Gulf war of 2003, the financial crisis of 2008, and the COVID-19 crisis, for example), economic uncertainty has become a key factor in determining production and even government decisions. Furthermore, the EPU can influence CO_2 emissions.

Conversely, economic policy uncertainty (EPU) can affect CO_2 in contradictory ways. On the one hand, economic uncertainty can inhibit investment and production, which reduces energy consumption and thus automatically reduces carbon emissions. On the other hand, EPU can stop 'companies' interest in alternative energies and energy transition, which are considered. According to them, high costs can be avoided usingtraditional and cheap energy sources of production using petroleum products, which increases carbon emissions. Despite the great importance of economic uncertainty, we find a relative scarcity of studies that deal with its impact on climate change, especially in major polluting countries such as India. India was included among other countries in a few studies, but no study estimated the impact of EPU on environmental quality in India.

As a result, we intend to contribute to the current literature on climate change by exploring the effect of economic uncertainty [as measured by the Ahir et al. (2022) index] and globalization [as measured by the Dreher (2006) index] on environmental quality measured by CO_2 emissions in the context of India over the last half-century, from 1970 to 2020. Notably, this is the first attempt to study the effect of uncertainty and globalization in one model on CO_2 emissions in one of the world's largest carbon emitter countries, using an augmented STIRPAT model. Latterly, India has experienced massive ups and downs in its economy due to the succession of Governments and their relentless pursuit of economic and social revival, especially in light of the country's high poverty rates. For this reason, the study attempts to gauge the impact of these trends by improving citizens' living conditions and increasing the country's welfare on environmental conditions. Consequently, developing countries like India have a vast and devastating impact on the environment in their early stages. Furthermore, the most important thing that has characterized India in these years is the rapidly growing economic growth, the exploding population, the enormous energy consumption, the great opening up to the outside, and the growing uncertainty in all aspects of economic life. Hence, this gives an essential edge to this study by looking at some of the most significant environmental impacts in India in recent years.

In addition, unlike previous research, this study employs the combined cointegration test proposed by Bayer and Hanck (2013) and the augmented ARDL (Auto-Regressive Distributed Lag) model proposed by McNown et al. (2018).

The rest of the paper is structured in six sections. Section 2 presents the literature review. Section 3 and Section 4 describe the data and methodology of the study. Study results are presented in Section 5, while section 6 highlights the conclusions and recommendations.

2 Literature review

Environmental degradation and climate change have become humanity's most pressing concerns in the last 20 years (UN Chronicle, 2007; Chan, 2018). According to numerous studies, our planet has experienced a considerable rise in global temperatures in recent years, which has become an enormous threat to all world countries regarding environmental, economic, social, and even security concerns. Besides, the economy is widely regarded as the primary and most significant contributor to environmental deterioration (Khan MB. et al., 2022a; Ullah I. et al., 2022a; Irfan et al., 2023; Zhang et al., 2023), as seen by natural resource depletion (Liang et al., 2022) on the one hand and rising energy use in industrial and agricultural activities on the other. As a result, economic studies to discover the most important causes of the continual deterioration of the environment have exploded in recent years.

Many studies examined how economic expansion affects carbon emissions. Mahmood et al. (2019) argue that economic growth may reduce environmental damage after a certain point, confirming an inverted U-shaped connection. In contrast, previous research discovered that economic growth and environmental damage are connected, and that industrial structure adjustments may mitigate climate issues (Wang et al., 2016). The energy-economic growth-pollution trilateral relationship is well known, as economic growth is based on energy consumption, while pollution is generated mainly by fossil fuels-generated energy (Al-Mulali et al., 2013; Wang et al., 2016). At the same time, the transition to renewable energy sources for fueling economic growth is widely recognized as one of the main solutions for ensuring both economic expansion and mitigation of climate change (Yuan et al., 2014; Wang et al., 2020; Abban et al., 2022; Ali et al., 2022; Khan I. etal., 2022b; Han et al., 2022). Meanwhile, investment openness is responsible for a surplus of carbon emissions associated with pollution-intensive industries, especially if the FDI destination is a developing or emerging country. Blanco et al. (2013) confirmed that after a certain threshold, the spillover effect will reduce environmental degradation (Xie et al., 2020). However, Haug and Ucal (2019) find evidence suggesting that FDI does not influence carbon emissions, while financial development and urbanization do. Previous research also supports the findings indicating financial development as a driver for carbon emissions (Zhang, 2011), even if indicates FDI as least threatening to the environment. On the other hand, Shahbaz et al. (2013) examine the impact of financial development on carbon emissions and find that the relationship benefits the environment, as the financial system may support green investments and energy-efficient technologies. Later, Boutabba (2014) also proves that financial development improves environmental degradation. Besides urbanization, population growth was considered as a feature influencing climate change. In this regard, Martínez-Zarzoso et al., 2007 argue that the increasing population attracts a higher environmental impact, yet it is not certain that a population reduction will reduce pollution. Other scholars emphasize the importance of population aging for carbon emissions, claiming that there is a positive relationship between the two features (Yu et al., 2018; Wang and Wang, 2021).

It is worth emphasizing that following the financial crisis of 2008, the world's economic activity entered a state of doubt and uncertainty. Similar to the Russian-Ukrainian war in early 2022, which produced great fear from all countries of the world, perhaps the rise in oil prices to 138 dollars per barrel is the best evidence of the impact of uncertainty on the global economy. As a result, researchers' interest in economic uncertainty has grown in recent years, particularly following Baker et al. (2016)'s study, which developed a statistical indicator to measure economic uncertainty created using the rate of recurrence of the word uncertainty in international newspapers as evidence of the rise or fall of uncertainty.

Despite the scarcity of research on the subject, the effect of (EPU) on CO_2 emissions has gained prominence in the last five years, leading to the conclusion that uncertainty plays a prominent role in institutional behavior toward environmental change. On the one hand, EPU may contribute to environmental degradation by increasing CO_2 emissions. However, many firms use cheap production methods that rely primarily on unclean energies to prevent any shocks that increase the cost of production in the long run (Jiang et al., 2019; Ulucak and Khan, 2020; Adams et al., 2020; Wang Q. et al., 2020; Amin and Dogan 2021; Anser et al., 2021; Atsu and Adams 2021; Syed and Bouri, 2021), while other studies considered the short run (Ashena and Shahpari, 2022).

Other studies, on the other hand, have found that the EPU may reduce CO_2 emissions while increasing environmental quality. In this case, high uncertainties may force institutions and companies to resort to clean energies to avoid any shortage in their supplies of fuels and petroleum products from global markets (Adeboyin and Zakari, 2020; Ahmed et al., 2021; Syed and Bouri, 2021; Liu and Zhang, 2022).

Even though India is one of the world's top ten carbon emitters, studies on the impact of economic uncertainty on CO_2 emissions in the country still need to be considered. This could be because the EPU index was not developed in India until the World uncertainty index indicator was proposed by Ahir et al. (2022). However, some studies on the subject, however, have focused on panel samples that included India. Anser et al. (2021), for example, evaluated the effect of WUI on CO_2 emissions in the top ten carbon emitter countries using pooled mean group ARDL (PMG-ARDL) modeling, depending on the STIRPAT model. The most notable finding of the researchers is the distinction between the short and long-term effects of WUI on CO_2 emissions, as economic uncertainty reduces carbon emissions in the short run, allowing for climate improvement. However, in the long run, the influence positively affects CO_2 emissions (Udeagha, M. C. and Muchapondwa, 2022), where economic uncertainty is regarded as a cause of environmental degradation in the study sample. Syed et al. (2022) studied the impact of EPU and geopolitical risks (GPR) on CO_2 emissions in BRICST countries from 1990 to 2015. The findings showed that EPU has a negative impact on CO_2 emissions at the lower and middle quantiles but a positive impact at the upper quantiles. Adams et al. (2020) investigated the causal link between EPU, CO_2 emissions, and energy consumption in ten resource-rich countries from 1996 to 2017. According to the findings, EPU has a long-term positive impact on CO_2 emissions, and a bidirectional causal relationship between EPU and CO_2 emissions was also pointed out.

Furthermore, Atsu and Adams (2021) explored the cointegration relationship between EPU, CO_2 emissions, energy consumption, financial development, innovations, and institutional quality in BRICS countries from 1984 to 2017. They used a cross-sectionally augmented ARDL model with panel data. According to the findings, EPU contributed to CO_2 emissions during the study period.

In recent years, globalization has become a significant aspect of the global economy since the world has become a small village because of the easy movement of capital, commodities, and individuals between the world's five continents. Hence, It should be unsurprising that globalization has a huge impact on the climate and the ecosystem (Aslam et al., 2021; Jahanger et al., 2022; Usman et al., 2022). Therefore, according to McAusland (2010), globalization hasthree probable consequences on CO_2 emissions. First, the scale effect states that globalization increases economic activities and subsequently surges energy consumption escalating CO_2 emissions. Second, the composition effect reveals that the impact of globalization on CO_2 emissions is linked to how globalization affects production structure. If globalization transforms the production structure from industrial to service sectors, CO_2 emissions fall; conversely, if globalization shifts the production structure from agricultural to industrial, CO_2 emissions rise. Third, in the technique effect scenario, globalization can affect production processes by introducing new technologies from international partners; these technologies could enhance energy efficiency by employing environmentally friendly procedures, leading to lower CO_2 emissions. In addition, Shahbaz et al. (2018) introduced a fourth effect known as the comparative advantage effect, which states that dirty industrial technologies can be transferred to developing and emerging countries in exchange for being rejected in their home countries; these countries' carbon emissions have soared.

Remarkably, there is a severe lack of research on the impact of globalization on CO_2 emissions in India, with only two studies found. Shahbaz et al. (2015) considered the relationship between globalization, as measured by the Dreher index (2006), energy consumption, CO_2 emissions, financial development, and GDP growth from 1970 to 2012. Unlike social and political globalization, the findings showed that economic globalization had a negative long-term impact on CO_2 emissions. In contrast to Shahbaz's (2015) findings, Sahu and Kumar (2020) used the ARDL model and the Dreher index (2006) to explore the effect of globalization on environmental quality from 1971 to 2014. According to this study, the results revealed that political and social globalization negatively influences CO_2 emissions. Also, Ullah S. et al., (2022b), studying two group's lower globalized economies (LGE) and highly globalized economies (HGE) found similar positive impact on CO_2 emmisions; however, economic globalization has a positive effect. In addition, Sharif et al. (2022) found that social globalization positively moderates the relationship between CO_2 emissions and economic output.

However, we only found a few additional articles in panel studies that looked at the impact of globalization on carbon emissions, including one from India. From 1972 to 2017, Khan Y. et al. (2022c) tested the association between globalization and CO_2 emissions in South Asian countries. Globalizationhad a positive impact on CO_2 emissions in all countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka), according to the findings. Juxtaposing, Haseeb et al. (2018) discovered the same result, revealing a positive link between globalization and CO_2 emissions in India and Russia but a negative one in Brazil, China, South Africa, and BRICS countries as a group. Conversely, Mehmood and Tariq (2020) concluded that globalization does not affect CO_2 emissions in India, Pakistan, and Bhutan in the long run, contrary to Bangladesh, Afghanistan, and Sri Lanka. Pata (2021) re-examined the same relationship in BRIC countries using Fourier ADL cointegration. The outcomes exposed no evidence of a cointegration relationship between the variables in India, in contrast to Brazil and China, with a positive impact of globalization on CO_2 emissions.

Furthermore, Muhammad and Khan (2021) discovered, using panel data from countries (developed and developing countries), that CO_2 emissions rise in industrialized countries while falling in developing countries as a result of economic globalization. Correspondingly, in a global data analysis covering 180 nations from 1980 to 2016, Farooq et al. (2022) confirmed the detrimental influence of globalization on environmental degradation, similar to Jahanger et al. (2022) results.

3 Data

To achieve our objective in this study, we use annual data from 1970 to 2020 in India to investigate the determinants of CO_2 emissions during the last half-century using the STIRPAT model. Therefore, our dependent variable is carbon dioxide emissions (CO_2) measured in metric tons, from Our World in Data and our independent variables are the world uncertainty index, from Economic Policy Uncertainty Index database, as well as the globalization index presented by Dreher (2006), from KOF Swiss Economic Institute website. Additionally, we include the three STIRPAT model components of technology, affluence, and population, as defined by Dietz and Rosa (1994). First, for the technology, we use the primary energy consumption (ENE) measured by oil equivalent consumption. Second, for affluence, we use the GDP *per capita* (GDP) and GDP *per capita* squared (GDP2), from World Bank to examine the Environmental Kuznets Curve EKC. Finally, for the population, we use population density (POP) by dividing the total population on the surface. Hence, the empirical model used this described in the equation below:

$$logCO2_t = \gamma_1 + \alpha_1 logGDP_t + \alpha_2 logGDP2_t + \alpha_3 logENE_t + \alpha_4 logPOP_t + \alpha_5 logWUI_t + \alpha_6 logGLO_t + \mu_t \quad (1)$$

Where γ_1 is the constant term (intercept), α_i are the slope coefficients, μ_t is the white noise of the estimation, and *log* denotes the logarithmic form.

4 Methodology

4.1 Combined cointegration test Bayer-Hanck (2013)

Since Engle and Granger (1987) developed it to evaluate the long-run association among variables, the cointegration concept has become dominant in time series analysis. Therefore, the Engle and Granger (1987) test (EG) demands that all the series under investigation have the same integration order I(1) or I(2). However the EG test can produce biased results due to its explanatory power properties. In 1991, Johansen introduced a novel approach (J) for examining cointegration relationships and solving EG test problems. The fundamental superiority of the J test on EG is that it detects multiple cointegration relationships among variables. Furthermore, Boswijik (1994) (Bo) presented a new procedure to estimate Error Correction Model (ECM) using F test, and Banerjee et al. (1998) (Ba) enforced the Boswijik work by the addition of ECM model based on *t*-test.

Based on these four tests, Bayer and Hanck (2013) combined all these tests in a single test to avoid possible different results for the unique tests. In this case, the Bayer-Hanck test gives us two test statistics as follows:

$$EG - J = -2[\ln\ (P_{EG}) + ln(P_J)] \quad (2)$$

$$EG - J - Bo - Ba = -2\sum \ln\ (P_i) = -2[\ln(P_{EG}) + ln(P_J) + \ln\ (P_{Bo}) + \ln\ (P_{Ba})] \quad (3)$$

Where, P_{EG}, P_J, P_{Bo}, and P_{Ba} indicate the probability values (*p*-values) for every single test, the Bayer-Hanck test uses the F statistic to test the existence of cointegration relationship to compare with critical values proposed by Bayer and Hanck, implying that the null hypothesis of no cointegration link should be rejected if the test statistic is higher than the critical value at α%.

4.2 Hatemi-J (2008) cointegration test

Conversely, the previously described cointegration tests presume that the estimated parameters do not vary over time (Hicham, 2020), implying that structural breaks in long-run relationships are discounted. Gregory and Hansen (1996) proposed a new process to test cointegration relationships with one structural break using three tests ADF (Augmented Dickey-Fuller), Za, and Zt. This procedure was developed by Hatemi-J (2008) by introducing two structural breaks in the equations below:

$$y_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + \beta_0' x_t + \beta_1' D_{1t} x_t + \beta_2' D_{2t} x_t + \varepsilon_t \quad (4)$$

Where D_{1t} and D_{2t} are the dummy variables defined for the structural breaks.

4.3 Augmented ARDL model

The augmented ARDL model (AARDL) is a new extension of the ARDL procedure presented by Pesaran et al. (2001). The standard auto-regressive distributed lags (ARDL) model examines two null hypotheses to detect cointegration relationships: the overall F-test for all the lagged variables and the *t*-test for lagged dependent variable. Nevertheless, Pesaran et al. (2001) assumed that the dependent variable must be an I(1) series, that no degeneration cases exist, and that the independent variable is exogenous. Remarkably, according to McNown et al. (2018), many researchers ignored these assumptions, resulting in inaccurate estimates. To avoid a generalized Dickey-Fuller equation when only the lagged dependent variable is significant, McNown et al. (2018) proposed a supplementary test to investigate the significance of the independent variables. This third test avoids the degenerate case reliance on the I(1) dependent variable notion. Given that all three tests accept significance, there is a strong confirmation of long-run association among the variables. Consequently, the model we used to examine the cointegration connection among our variables, as well as long and short-run estimation, for our framework is as follows:

$$\begin{aligned}\Delta \ln CO2_t = &\gamma_1 + \alpha_1 CO2_{t-1} + \alpha_2 GDP_{t-1} + \alpha_3 GDP2_{t-1} + \alpha_4 ENE_{t-1} \\ &+ \alpha_5 POP_{t-1} + \alpha_6 WUI_{t-1} + \alpha_7 GLO_{t-1} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{1i} \Delta CO2_{t-i} + \sum\nolimits_{i=1}^{p} \beta_{2i} \Delta GDP_{t-i} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{3i} \Delta GDP2_{t-i} + \sum\nolimits_{i=1}^{p} \beta_{4i} \Delta ENE_{t-i} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{5i} \Delta POP_{t-i} + \sum\nolimits_{i=1}^{p} \beta_{6i} \Delta WUI_{t-i} \\ &+ \sum\nolimits_{i=1}^{p} \beta_{7i} \Delta GLO_{t-i} + \tau_i D_t + \mu_t \end{aligned} \quad (5)$$

Where γ_1 is the intercept of the equation; β_{ji} represents the short-run estimators; α_j indicates the long-run estimators and μ_t is the white noise of estimation while Δ representing the first difference operator. In addition, D_t denotes possible structural breaks in the model. Thus, the three hypotheses are as bellow:

First, The null hypothesis for the overall F test on all variables is H_{0A}: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = 0$;

Second, the null hypothesis for the *t*-test on only the dependent variable is H_{0B}: $\alpha_1 = 0$;

Third, the F-test on independent variables is: H_{0A}: $\alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = 0$.

TABLE 1 Unit root tests results.

Variables	Bootstrap ADF		Zivot-Andrews		Lumsdain-Pappel	
	Test	5% cri. v	Test	Break	Test	Breaks
CO_2	−1.306	−1.806	−1.488	2014	−2.799	2001–2014
Δ (CO_2)	−4.416***	−3.025	−6.210***	2012	−7.110**	1997–2012
ENE	−0.935	−1.771	−3.662	1988	−4.183	1988–2007
Δ (ENE)	−6.845***	−3.093	−8.535***	1991	−9.382***	1988–2004
POP	−1.446	−3.791	−1.254	1994	−2.652	1985–2003
Δ (POP)	−4.001***	−2.249	−5.535**	2015	−6.872**	2007–2014
GDP	1.908	−1.948	−3.531	1979	−4.355	1979–1991
Δ (GDP)	−4.965**	−2.996	−7.158***	2015	−6.850**	1990–2014
GDP2	2.220	−1.936	−3.281	1991	−3.869	1979–1991
Δ (GDP2)	−4.274**	−2.996	−6.628***	2015	−6.858**	2004–2014
GLOB	−0.608	−2.585	−2.456	1979	−6.254	1989–2008
Δ (GLOB)	−3.610**	−3.086	−5.384**	1993	−7.056**	1981–1993
WUI	−4.071***	−3.139	−5.177**	2000	−6.329*	1995–2012
Δ (WUI)	−10.102***	−3.054	−10.428***	1997	−10.624***	1982–1997

Δ indicates the first differences; *, **, *** represents significance at 10, 5% and 1% respectively; Critical values for the ADF test are simulated based on 10,000 bootstrap replicates. For the Zivot-Andrews test, critical values are −5.57(1%), −5.08(5%) and −4.82(10%); For theLumsdain-Pappel test, critical values are −7.19 (1%), −6.75 (5%) and −6.48 (10%).

5 Findings and discussion

5.1 Stationarity tests

Because the ARDL methodology demands that all variables must be I(0) or I(1) series with no I(2) series, the first stage in our investigation is to guarantee that our variables are not stationary at the second difference. Therefore, to avoid any misleading outcomes, we use three-unit root tests. The first is the bootstrap unit root test proposed by Park (2003) ADF to obtain bootstrap critical values for each variable. Second, to handle probable structural breaks in the data, the Zivot-Andrews (ZA) (1992) and Lumsdain-Pappel (LP) (1997) tests are also used. Table 1 shows the results, and it is evident that our series is not stationary at their levels, excluding the WUI, which is stationary at its level by the ADF and ZA tests but not by the LP test, which has two structural breaks. Accordingly, all the series are I(1) series, and there is no I(2) variable. Hence, we can run the ARDL procedure in addition to both Bayer-Hanck and Hatemi tests to test the cointegration link in our series.

5.2 Cointegration tests

Once we have confirmed the integration order of the variables, which are I(1) series, it is important to examine the cointegration behavior to explore the long-run association between them. This paper demonstrates the cointegration between variables by using three different tests. Initially, we use the combined test proposed by Bayer and Hanck (2013) based on four previous tests. Hatemi-J's (2012) test with two structural breaks accounts for possible long-term relationship breakdowns, as we cannot use Maki's (2012) tests for five structural breaks due to the short study period. McNown et al. (2018) presented the Augmented ARDL (AARDL) instead of the standard ARDL to support the results of the first two tests. A

TABLE 2 Co-integration tests results.

Bayer-Hanck test				
Tests	Engel-GrangeEG	Johansen J	Banerjee BA	Boswijk BO
Test statistic	−3.748	70.098***	−3.765	25.208**
p-value	0.470	0.000	0.165	0.048
EG-J	56.769***	5% critical value 10.352		
EG-J-BA-BO	66.437***	5% critical value 19.761		
Hatemi test				
Tests	Test statistic	5% critical value	Break 1	Break 2
ADF	−9.158***	−7.903	1987	2004
Zt	−11.444***	−7.903	1990	2004
Za	−135.968**	−123.870	1990	2004
AARDL				
Hypothesis	Test statistic	I (0) 5% crit. val	I (1) 5% crit. val	
F overall	4.292**	2.764	4.123	
t dependent	−4.867**	−2.86	−4.38	
F independent	4.998**	2.32	4.03	

*** symbolizes significance at 10, 5%, and 1% respectively.

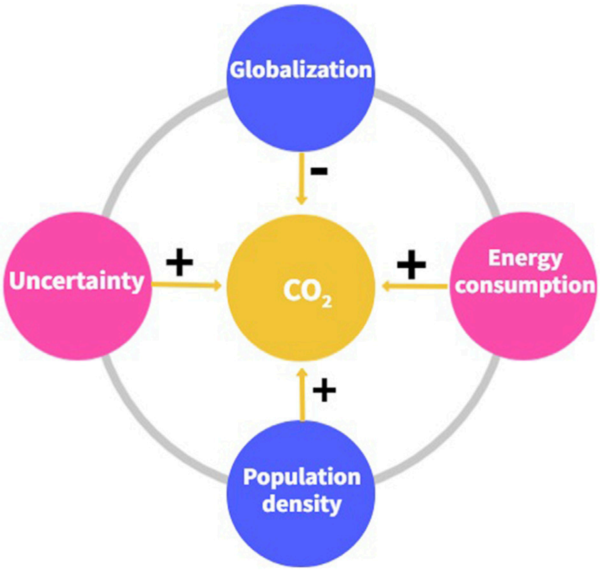

FIGURE 1
Graphical presentation of empirical results.

Bayer-Hanck test revealed that EG-J test statistics are greater than critical values at a 1% t significance level, as illustrated by Table 2's results, which unquestionably showed long-run relationships between variables tested under the three tests. Using three tests with a 5% significance level, the Hatemi tests also revealed the cointegration nexus with two structural breaks in 1990 and 2004.

Moreover, the results showed evidence of rejecting the three null hypotheses of the AARDL procedure at a 5% significance level using bootstrapping critical values with 10,000 replications. Consequently, the alternative hypothesis of the cointegration relationship among our variables should be accepted at a 5% significance level, meaning that our variables have the same long-term behavior and do not diverge from one another.

5.3 Long-run estimations

Following that, under the assumption of a cointegration relationship, we apply three estimating approaches to estimate the long-term impacts in our model: FMOLS, DOLS. The fully modified ordinary least square (FMOLS) regression is developed as a residual-based test with better efficiency in estimating results for cointegrated variables (Pedroni, 2001). DOLS that are very useful in the case of co-integrated variables with I(1) process, in addition to and AARDL, with the introduction of structural breaks for the first two estimations. In this context, the long-run estimations yielded the following results. According to the empirical results (Figure 1), any increase in energy consumption by 1% increases CO_2 emissions by 0.98%–1.27% in India, as seen in Table 3, which is in line with the results of Shahbaz et al. (2021), Jayasinghe and Selvanathan (2021) and Kanjilal and Ghosh (2013). There was a significant energy demand across all sectors, particularly manufacturing, industry, and transportation, which supported economic growth and thus increased carbon emission rates. As a result, the direct impact of energy consumption on environmental degradation can be seen in the post-liberalization period.

Furthermore, the results revealed the existence of an inverted U shape of EKC based on the positive GDP coefficient and the negative GDP square coefficient. CO_2 emissions rise monotonically with GDP up to 3.44 (1.6174/2*0.235 = 3.44) but diminish once income exceeds this level. However, it is essential to note that economic growth throughout the study period did not reach this threshold. Besides, the findings revealed that GDP is the most critical determinant in environmental degradation in India over the research period, with any rise in GDP of 1% leading to an upsurge in CO_2 emissions up to 2.53%. This result is in line with Ohlan's (2015) and Akalpler and Hove, 2019 results.

Economic globalization reduces India's CO_2 emissions by 0.13%–0.21% for every one percentage point increase in Economic globalization as determined by the three estimation methods. For Shahbaz et al. (2015), this study supported their findings in India, and Zaidi et al. (2019) findings in the Asia Pacific Economic Cooperation countries. Thus, given the negative correlation between globalization and CO_2 emissions, it is clear that new approaches to entering global markets and gaining new trading partners can help improve environmental quality.

Moreover, the results indicate that the world uncertainty index affects CO_2 emissions in India only with the dynamic OLS regression, whereas the increase in WUI by 1% escalates CO_2 emissions by 0.0086%. Principally, the contribution of WUI to environmental degradation can be explained by two possible mechanisms, as described by Muhammad and Khan, 2021. First, uncertainty can be seen as an impediment to R&D, innovation, and the transition to renewable energy sources to prevent uncertainty shocks that might hinder economic growth. As a result, these precautionary policies increase carbon emissions. Second, a high WUI encourages firms to adopt traditional production methods, such as machines that use oil, gas, or coal energy sources to minimize production costs and absorb uncertainty shocks that can raise raw material prices, increasing CO_2 emissions.

Finally, population density positively influences environmental degradation only, with AARDL estimation showing that 1% augmentation in population density escalates CO_2 emissions by 0.78% in India. Additionally, the R-squared coefficient shows that the variations of the independent variables explain 99.9% of the variation in dependent variables.

5.4 Short-run estimations

As shown in Table 4, we used two error correction models to detect the short-run effect on CO_2 emissions. The best outcomes are found in the AARDL-ECM (AARDL Error Correction Model) estimation, which has an R-squared of 0.7336, and most estimators are significant. Notably, the results are presented with only one lag because the higher lags are insignificant. An important finding is that the model corrects 73% of its deviations from long-run equilibrium each year, which is statistically significant at 1%, meaning that after any shock, the system will be back to its equilibrium state after 17 months. This result is in line with the

TABLE 3 Long run estimation results.

Variables	FMOLS		DOLS		AARDL	
	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability
ENE	1.0715***	0.000	0.9835***	0.000	1.2739***	0.000
GDP	1.6174***	0.007	1.3777**	0.013	2.5350***	0.008
GDP2	−0.2350**	0.011	−0.2006**	0.012	−0.397***	0.007
GLO	−0.1355**	0.021	−0.1561***	0.000	−0.2168***	0.006
POP	−0.3524	0.195	−0.0890	0.668	0.7889**	0.038
WUI	0.0007	0.601	0.0086***	0.000	0.0004	0.8347
C	3.5705***	0.000	3.7867***	0.000	1.3268***	0.000
D1990	−0.0030	0.660	−0.0179***	0.000	/	/
D2004	−0.142**	0.032	0.0020	0.545	/	/
R-squared	0.9995		0.9999		0.9997	
LM test	/	/	/	/	0.0577	0.944
ARCH	/	/	/	/	0.2408	0.787

D1990 and D2004 structural breaks obtained from Hatemi tests; LM test Lagrange Multiplier test for autocorrelation of errors and ARHC is the heteroscedasticity test of errors.

TABLE 4 ECM model for short-run estimation results.

Variables	ECM		AARDL-ECM	
	Coefficient	Probability	Coefficient	Probability
ECT	−0.648***	0.000	−0.7903***	0.000
Δ(ENE)	0.6704***	0.000	0.6421***	0.000
Δ(GDP)	0.3944	0.797	2.0034**	0.013
Δ(GDP2)	−0.0252	0929	−0.3141**	0.011
Δ(GLO)	−0.1158	0.428	−0.1714**	0.011
Δ(POP)	0.5542	0.809	0.6234**	0.037
Δ(WUI)	0.0001	0.851	0.0003	0.835
C	0.0018	0.932	2.2314**	0.032
D1990	−0.0008	0.860	−0.0132*	0.070
D2004	0.0003	0.948	−0.0009	0.886
R-squared	0.5752		0.7336	

ECT denotes the Error Correction Term for adjustment speed and Δ denotes the differences series.

cointegration outcomes in Table 2, which shows that the model corrects 73% of its deviations from long-term equilibrium each year. The ECM method is remarkable in that it achieves the same results in the short and long term. However, estimates show that in the short term, energy consumption, GDP *per capita*, and population density worsen environmental degradation, whereas globalization decreases CO_2 emissions and improves environmental quality. Furthermore, the EKC hypothesis testing revealed an inverse U shape with a threshold of 3.19 in the short run.

6 Conclusions

Environmental quality and climate change have become hot topics among scholars in all scientific fields in recent decades due to their impact on human health and economic development. Hence, this paper investigated the key determinants of CO_2 emissions as one of India's most significant environmental degradation characteristics over the last half-century, 1970–2020. Furthermore, using a STIRPAT model, we investigated the relationship between carbon dioxide emissions and energy use, GDP *per capita*, population density, and the world uncertainty and globalization indexes. We used various cointegration techniques such as Bayer and Hanck (2013), Hatemi-j (2008), and Augmented ARDL methods to explore the presence of a long-run connexion between our variables. Moreover, the bootstrap ADF test (2003), Zivot and Andrews (1992), and Lumsdain and Pappel (1997) tests were employed to explore the integration order of the series in order to deal with unit roots and structural breaks.

The tests used in our empirical results confirmed the cointegration relationship among our variables. There was a negative correlation between carbon emissions and GDP *per capita* square after a threshold of 3.44, indicating that India has an inverse U-shaped EKC hypothesis. However, the threshold was not reached yet, which justify further economic growth policies. For not affecting the environment further, it is critical for these policies to include carbon mitigation goals and environmental protection goals. The positive link between GDP *per capita* and CO_2 emissions is responsible for this. There is also evidence that CO_2 emissions are linked to energy consumption and population density in both the long and short term. As a result of the Indian government's post-liberalization policies over the last fifty years, particularly the expansion of energy demand, especially for energy derived from oil, gas, and coal sources, energy use and population growth are key determinants of environmental degradation in India.

In addition, the findings revealed that the economic uncertainty index contributes to an escalation in carbon dioxide, particularly in the long run. This is due, as previously stated, to firms adopting precautionary policies to avoid uncertainty shocks by reducing production costs through the use of non-environmentally friendly production methods. Conversely, all of the measuring methodologies utilized in our study demonstrated that globalization contributes to enhancing environmental quality in India in the short and long term. Hence, this result emphasizes the necessity for the Indian government to pursue policies that promote more trade openness by entering new markets and cooperating with new trading partners, imposing at the same time a strict environmental protection regulation to promote new technologies, better energy efficiency and carbon emissions mitigation targets.

While the study emphasizes the impact of uncertainty on environmental degradation and the contribution of globalization to curb carbon emissions, it has some limitations. Globalization could be analyzed on three dimensions—economic, social, and overall—to better understand the drivers that policymakers may use in mitigating environmental issues but also in shaping economic growth options. Future research could be oriented to describe the impact of globalization on environmental degradation, economic growth, and social welfare to comprise all three major development needs of India.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://worlduncertaintyindex.com/data/ https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html https://data.worldbank.org.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer MU declared a past co-authorship with the author DB to the handling editor.

Publisher's note

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