The Impact of Innovation Technology on Carbon Emissions in India

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Abstract

Numerous studies have examined the determinants of CO_2 emission. However, earlier research has neglected to analyse the emission of CO_2 resulting from the exchange of innovation technology. The present work contributes to the research stream by examining the relationship between innovation technology and environmental degradation in India from 1980 to 2021 during the time period of study. On the basis of the Auto Regressive Distributive Lag (ARDL) model and the Vector Error Correction (VECM) Granger Causality approach, the main finding is that innovation technologies are the primary contributors to India's long-term CO_2 emission. Short-term causality emerges from one-way causation between innovation technology and CO_2 emissions. Additionally, a long-term feedback hypothesis between energy usage and CO_2 emissions is rejected. Numerous critical tests are conducted to assure the stability of the model and the dependability of policy-relevant conclusions. This study proposes that the Indian government should invest more in research and development to increase its innovative technological power, which would be beneficial for environmental protection.

Keywords: carbon emissions, innovation technology, ARDL bound testing, VECM

1. Introduction

Both economists and eco-activists now consider environmental degradation to be a major topic of discussion. Deforestation, polluting emissions from the burning of fossil fuels and excessive use of these are central to the argument that human activity is causing global environmental change. Wigley [1] stated that a pre-industrial CO_2 level somewhere in the range of 260-270 ppmv, well below the 290 ppmv figure that is more commonly cited. The annual rate of global carbon dioxide emissions from fossil fuel combustion and industrial processes rose in 2021 to a new record high. Using the most recent official national data and publicly available energy, economic, and weather data, the IEA estimated that by 2020, emissions will have increased by 6%, totalling 36.3 Gt. Furthermore, in 2021, global energy consumption is expected to rise by 4.6%, more than making up for the 4% drop in 2020 and propelling consumption 0.5% higher than in 2019. Global energy demand is expected to increase by 3.4% in 2020, with nearly 70% of that increase coming from emerging markets and developing economies [2]. According to Feulner [3], climate change is the world's greatest problem in the 21st century. When it comes to global problems, climate

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change is one that cuts across many disciplines. Global water supplies, agricultural output, human health, and energy infrastructure are just some of the areas that could be affected by climate change. In turn, how we generate power and nourish ourselves has a major impact on the global climate.

India has its current focus on a path of economic growth that experts predict will bring change in economic viability. Current energy consumption in India's is roughly a third of the global average and significantly lowers than the developed world's average. India reliance on coal and other fossil fuels for energy is substantial. Over the past 15 years, per-capita energy consumption has more than doubled, but nearly 240 million still lack access to a reliable, affordable energy source. Over the last decade, India's energy consumption has increased at about 6% annually. Although non-fossil fuel production has increased rapidly, the BP Energy Outlook 2035 predicts that India will have the fastest growth in energy consumption of any major economy. By 2035, experts predict a 128% increase in global energy consumption [4]. Govindaraju and Tang [5] found the two-way causal relationship between economic expansion and CO_2 emissions, and between CO_2 emissions and coal use. However, only a unidirectional Granger causality links economic growth and coal consumption in India. Ohlan [6] found a correlation between India's trade liberalisation and increased carbon emissions. Sahu et al. [7] found that in India, while economic globalisation has a positive but insignificant effect on CO_2 emissions, other forms of globalisation, including overall globalisation, social globalisation, and political globalisation, all have negative effects.

The scale effect, the composition effect, and the technique effect are the three main ways trade liberalisation can affect the total amount of emissions. First, the scale effect increased economic activity due to free trade but also increased CO_2 emissions. This greater economic activity will necessitate increased energy consumption, which in turn will increase the emissions of greenhouse gases. Secondly, the composition effect describes how the structure of a country's production shifts as a result of trade opening in response to changes in relative prices, and how this shift affects emission levels. A country's comparative advantage determines how its production structure shifts as it liberalises. Changes in the composition of production in an economy that is opening its markets to trade may be a reaction to differences in environmental regulations between countries. Finally, improvements in goods and services production techniques brought about by the technique effect lead to lower emission intensities in the final output. This is the main way freer trade can help reduce greenhouse gas emissions [8]. Concerning climate change has been a result of the substantial increase in international trade and investment flows in recent years. The allocation of physical resources and the spread of technology worldwide are heavily influenced by foreign direct investment (FDI), trade, and interaction among countries in other forms, such as intellectual property rights, royalty and licencing fees. There is a possibility that technology transfer will increase pollution levels in the environment. Export growth and the resulting economy-wide scale effect may add to CO_2 emissions.

The results of the current study add to the body of knowledge in a number of ways. To begin, none of the studies in the literature mention the impact of imported technology on CO_2 emissions. This study makes an effort to examine the impact of foreign technology on India's CO_2 emissions. The second phase involves new variables to the model, such as energy consumption, foreign direct investment, and trade, all of which may have an impact on CO_2 emissions. To improve empirical results and resolve the specification problem, this study includes additional factors in environmental quality assessments. Additionally, policymakers would benefit from formulating a comprehensive environmental policy for sustainable economic development. Lastly, we employ innovative and advanced techniques, namely the ARDL bounding testing approach and the innovative accounting approach.

The remainder of the study is structured as follows: Section 2 provides a literature review; Section 3 describes the methodology and model specification; and Section 4 discusses the findings and provides a conclusion. Section 5 is the study's conclusion.

2. Literature Review

In recent years, a substantial amount of research has been conducted on the relationship between energy consumption and carbon emission using various control variables. Multiple econometric approaches have been used to examine the connection between economic development, energy consumption, and environmental degradation, with varying conclusions drawn from cross-country and panel data. Relevant studies have been conducted in Pakistan [9], South Africa [10], Sri Lanka [11], Turkey [12], Nigeria [13], USA [14], China [15], France [16], Malaysia [17], India [18], South Korea [19], SAARC nations [20], BRICS countries [21], industrialized and industrializing countries [22], OECD countries [23], and 106 countries classified according to their income levels [24]. All of the authors demonstrate that reliance on energy consumption is a significant cause of carbon emissions.

The connection between energy consumption and CO_2 emission has been the subject of extensive research. Numerous researchers have determined that energy consumption enhances CO_2 emissions which is a potential contributor to environmental pollution. Various econometric techniques have been used in the literature to test the relationship between energy consumption and CO_2 emission, using time series data and the results indicate that energy consumption is a potential determinant of CO_2 emission [25–27]. Utilizing numerous control variables, the relationship between energy consumption and CO_2 emissions is examined. In addition, previous research has identified both unidirectional and bidirectional causal relationships between energy consumption and CO_2 emissions. Alam et al. [28], incorporating economic and population growth, conclude that there is a positive relationship between energy consumption and CO_2 emissions in India over the long term. Moreover the energy consumption bi-directionally Granger causes carbon emission in short-run. Acaravci and Ozturk [29] utilized an autoregressive distributed lag (ARDL) bounds testing approach to cointegration to investigate the connection between carbon dioxide emissions, energy consumption, and economic growth across 19 European countries. Evidence of a long-run relationship between carbon emissions per capita, energy consumption per capita, and economic growth is provided by the bounds F-test for cointegration.

Furthermore, studies conducted in Denmark, Germany, Greece, Italy, and Portugal found a positive long-run elasticity estimate of emissions with respect to energy consumption at the 1% significant level. In Thailand, Boontome et al. [30] applied a causality test to show that the use of nonrenewable energy sources increased carbon emissions uni-directionally in short-run. Bildirici [31] found the both the short and long run relationship among energy consumption and carbon emissions in USA through the use of the bound test method of cointegration. The MWALD and Rao's F tests were used to establish the causal connection. There is proof of unidirectional causality between energy consumption and CO_2 emissions, as determined by Rao's F tests. Waheed et al. [32] conducted a literature survey and found that higher energy consumption has been reported as the primary cause of carbon emission in both developing and developed countries. Gorus and Aydin [33] demonstrated that over the long and intermediate term, energy consumption has a reciprocal effect on emission levels.

Additionally, short-term evidence supports a unidirectional Granger causality between energy consumption and emissions in MENA countries. Wang et al. [34] examined the long-run relationship between energy consumption and carbon emission in China by cointegration and examining the unidirectional relationship between the two variables using the granger causal test. Following the same methodology in Indonesia, Hwang and Yoo [35] implied that there is a direct correlation between increased energy consumption and increased CO_2 emissions, and that increased CO_2 emissions also stimulate additional energy consumption. Furthermore, Soytas et al. [36] supported that energy consumption Granger causes carbon emissions in the US. Sharif et al. [37] proved that all variables are integrated in the long run, as shown by the CIPS unit root test, bootstrap cointegration, Pedronicointegration, FMOLS, and heterogeneous panel causality methods on 74 nations. The results also demonstrated that the consumption of nonrenewable energy has a positive impact on environmental degradation. Using time series econometric methodology, this paper examines the causal relationships between energy consumption, pollution emission, and economic growth in Nepal. When energy consumption and carbon emissions are used as dependent variables, both the Johansen cointegration and ARDL (Autoregressive Distributed Lag) bounds tests indicate the presence of two cointegrating vectors. Granger causality tests indicate the existence of a long-term bidirectional causal relationship between energy consumption and carbon emission and vice versa [38].

While FDI is a major contributor to environmental degradation, some studies have shown conflicting results when it comes to its impact on the state of the environment. In this regard, Gökmenoğlu and Taspinar [39] examined the impact on FDI on carbon emissions and found The results of the Toda-Yamamoto causality test indicated a bi-directional relationship between FDI, energy use, and CO_2 emissions in Turkey. Blanco et al. [40] used 18 Latin American countries from 1980–2007 and found causality between FDI in pollution-intensive industries and CO_2 emissions per capita. Omri et al. [41] examined how FDI affects carbon emissions in Europe and Central Asia, Latin America and the Caribbean, and the Middle East, North Africa, and sub-Saharan Africa. Their study found bidirectional causality between FDI inflows and CO_2 except for Europe and North Asia. Using Granger causality tests, Hoffmann et al. [42] examined the connection between foreign direct investment (FDI) and pollution in 112 countries over a 15-28 year period. The main findings revealed that the two variables have different causality relationships depending on the level of development in the host country. However, in the cases of India, Iceland, Panama, and Zambia, the pollution halo hypothesis stating that FDI has positive environmental effects was supported [43]. Jebli et al. [44], who examined the impact of FDI on carbon emissions in a panel of 22 Central and South American nations, discovered that FDI contribute to the reduction of emissions. Rafique et al. [45], using information collected between 1990 and 2017, examined how FDI has affected carbon emissions in BRICS countries by the Augmented Mean Group (AMG) estimator and proved that foreign direct investment in BRICS countries has a negative and statistically significant substantial connection with CO_2 emissions. The study utilized the Dumitrescu and Hurlin panel causality test to determine the direction of causality. There is a one-way causal relationship between foreign direct investment and carbon emissions, according to the findings. Prior research has also examined the connection between trade openness and environmental quality. Conclusions regarding the role of international trade are mixed. In Tunisia, the long-term estimates of carbon emissions per capita in relation to trade openness were predicted to be positive [46]. Hossain [47] conducted study for the panel of newly industrialized countries (NIC) and conclude that this short-term causal relationship between trade openness and carbon dioxide emissions is unidirectional. However, in the long run, it is determined that trade openness is generally beneficial. Destek etla. [48] analysed 10 countries in Central and Eastern Europe to determine how trade openness affects their carbon emissions (CEECs). They found that an increase of 1% in trade openness resulted in a 0.0686% decrease in carbon dioxide emissions. In BRICS countries, Sebri and Ben-Salha [49] found the long-run relationship among trade openness and carbon dioxide emissions by using the ARDL bounds testing approach to cointegration and the vector error correction model (VECM). The openness of trade has a detrimental effect on CO_2

emissions [50,51]. In terms of the trade-pollution nexus, the United States of America, Canada, Iran, and France hold a unidirectional causality running from increased economic growth to increased trade openness, which in turn leads to increased CO_2 emissions [52]. Thailand, Turkey, India, Brazil, China, Indonesia, and Korea had co-integrated among trade openness and carbon emission [53]. Moreover, trade openness is not only one of the primary long-term determinants of carbon emissions, but also has a causal relationship with it.

Based on a review of the existing literature, it is clear that the majority of researchers are interested in studying the connection between CO_2 emissions and energy consumption by employing a variety of explanatory variables, as well as FDI and trade by utilising panel and cross-sectional data. However, the allocation of physical resources and the spread of technology around the world are heavily influenced by international trade and other forms of interaction between countries, such as intellectual property rights and royalty and licencing fees (a proxy for imported technology). In the field of environmental pollution, this area of study is still under-researched. Moreover, the empirical results, based on a case study of the transfer of the passive home concept from Germany to China, demonstrate that domestic rather than foreign players have determined the scope for collaboration and the aim of the technology, leading to the acceptance of a version of the technology that best suits domestic political-economic objectives [54]. These results provide fresh insights into the spatial component of socio-technical transitions and imply that low-carbon technology transfer is becoming geographically complex. Following the methodology of previous studies [55], this investigation uses multivariate analysis on disaggregated data for imported technology within a unifying framework to examine the role of imported technology in environmental degradation in India. The research in this article employs an ARDL-bound testing strategy to determine both long and short-run estimates for India between the years 1980 and 2020. The VECM Granger causality method can be used to determine the direction of causality. The validity of the VECM Granger causality test is evaluated with the help of an innovative accounting approach (IAA).

3. Econometric methodology and data source

The current study aims to analyse how India's use of imported technology affects its CO_2 output. Using the methodology of [51] and [16], the current study employs a multivariate framework that permits the incorporation of control variables to investigate how the introduction of new technologies affects environmental degradation. A number of studies have examined the correlation between pollution as an endogenous variable and a variety of exogenous and control variables. This study uses the following equation to investigate the connections between India's environmental degradation, energy consumption, FDI, and trade.

$$CO_2 = \int (E, T, F, I) \tag{1}$$

This study uses a multivariate econometric framework to examine the interconnections between imported technology, energy consumption, trade ratio, foreign direct investment, and environmental degradation, following the lead of [54]. The following are the parameters of the econometric model used in this investigation:

$$CO_{2t} = \beta_0 + \beta_{1t} E + \beta_{2t} T + \beta_{3t} F + \beta_{4t} I + \varepsilon_t \tag{2}$$

The transformed log-linear functional form of the model is shown below.

$$LOGCO_{2t} = \beta_0 + \beta_{1t} LOGE_t + \beta_{2t} LOGT_t + \beta_{3t} LOGF_t + \beta_{4t} LOGI_t + \varepsilon_t \tag{3}$$

CO_2 represents per capita carbon dioxide emissions, E represents per capita energy consumption, T represents trade ratio (sum of export and import), I represents innovation technologies measured as royalty and licensing fee, F represents foreign direct investment, ε is a residual term, and t is the period.

Several estimation techniques have been used by researchers to establish cointegration between CO_2 emission and its determinants, such as the residual-based approach by [55] and the full information maximum likelihood method described by [56].In order to examine the durability of the above mention test, the third test created by [57] has been used. The advantages of the autoregressive distributed lag (ARDL) bounds testing approach to cointegration led this study to use it to investigate whether or not a long-run relationship exists between imported technology and CO_2 emissions. When looking at it from a statistical perspective, an ARDL specification is the same thing as a standard error correction model. Moreover, it is likely to generate different standard errors, because ARDL estimates of standard errors are considered unbiased. It is possible to estimate both the long-run and short-run dynamics simultaneously using the ARDL bound testing approach by linear transformation. Because of this reason ARDL is better suited for this study than other cointegration methods. The ARDL bounding testing method is preferred regardless of whether the variables are I (0) or I (1). Furthermore, the ARDL bound testing strategy proved especially helpful for this research because it is the most effective method for identifying the long-term connection even when working with a relatively small data set. The following clarifies the ARDL bounding testing technique developed for the variable of interest:

$$\begin{aligned}&\Delta \log CO_2 = \beta_o CO_2 + \sum_{k=1}^{n} \beta_{1k} \Delta \log CO_{2(t-k)} + \sum_{k=0}^{n} \beta_{2k} \Delta \log E_{(t-k)} + \sum_{k=0}^{n} \beta_{3k} \Delta \log F_{(t-k)} + \\ &\sum_{k=0}^{n} \beta_{4k} \Delta \log T_{(t-k)} + \sum_{k=0}^{n} \beta_{5k} \Delta \log I_{(t-k)} + \delta_{1co_2 \Delta Log co_{2(t-1)}} + \delta_{2co_2 \Delta \log_{(t-1)}} + \delta_{3co_2 \Delta log F_{(t-1)}} + \\ &\delta_{5co_2 \Delta \log T_{(t-1)}} + \delta_{6co_2 \Delta log I_{(t-1)}} + \varepsilon_{1t}\end{aligned} \tag{4}$$

Both the dependent and independent variables in an equation must have the same value. The following equations represent each independent variable.

$$\begin{aligned}&\Delta \log E = \beta_o E + \sum_{k=1}^{n} \beta_{1k} \Delta \log E_{(t-k)} + \sum_{k=0}^{n} \beta_{2k} \Delta \log CO_{2(t-k)} + \sum_{k=0}^{n} \beta_{3k} \Delta log F_{(t-k)} + \\ &\sum_{k=0}^{n} \beta_{4k} \Delta \log T_{(t-k)} + \sum_{k=0}^{n} \beta_{5k} \Delta \log I_{(t-k)} + \delta_{1E \Delta log CO_{2(t-1)}} + \delta_{2E \Delta log E_{(t-1)}} + \delta_{3E \Delta \log F_{(t-1)}} + \\ &\delta_{4E \Delta \log T_{(t-1)}} + \delta_{5E \Delta \log I_{(t-1)}} + \varepsilon_{1t}\end{aligned} \tag{5}$$

$$\begin{aligned}&\Delta log T_{=} \beta_o T + \sum_{k=1}^{n} \beta_{1k} \Delta \log T_{(t-k)} + \sum_{k=0}^{n} \beta_{2k} \Delta \log E_{(t-k)} + \sum_{k=0}^{n} \beta_{3k} \Delta \log F_{(t-k)} + \\ &\sum_{k=0}^{n} \beta_{4k} \Delta log CO_{2(t-k)} + \sum_{k=0}^{n} \beta_{5k} \Delta log I_{(t-k)} + \delta_{1T log T_{(t-1)}} + \delta_{2T \Delta log E_{(t-1)}} + \\ &\delta_{3T \Delta \log F_{(t-1)}} + \delta_{4T \Delta log CO_{2(t-1)}} + \delta_{5T \Delta log I_{(t-1)}} + \varepsilon_{1t}\end{aligned} \tag{6}$$

$$\begin{aligned}&\Delta logI = \beta_o I + \sum_{k=1}^{n} \beta_{1k} \Delta logI_{(t-k)} + \sum_{k=0}^{n} \beta_{2k} \Delta logE_{(t-k)} + \sum_{k=0}^{n} \beta_{3k} \Delta logF_{(t-k)} + \\ &\sum_{k=0}^{n} \beta_{4k} \Delta logT_{(t-k)} + \sum_{k=0}^{n} \beta_{5k} \Delta logCO_{2(t-k)} + \delta_{1I\Delta logI_{(t-1)}} + \delta_{2I\Delta logE_{2(t-1)}} + \\ &\delta_{3I\Delta logF_{2(t-1)}} + \delta_{4I\Delta logT_{2(t-1)}} + \delta_{5I\Delta logCO_{2(t-1)}} + \varepsilon_{1t}\end{aligned} \tag{7}$$

$$\begin{aligned}&\Delta logF = \beta_o F + \sum_{k=1}^{n} \beta_{1k} \Delta logCO_{2(t-k)} + \sum_{k=0}^{n} \beta_{2k} \Delta \log E_{(t-k)} + \sum_{k=0}^{n} \beta_{3k} \Delta \log F_{(t-k)} + \\ &\sum_{k=0}^{n} \beta_{4k} \Delta \log T_{(t-k)} + \sum_{k=0}^{n} \beta_{5k} \Delta logI_{(t-k)} + \delta_{1F\Delta logF_{(t-1)}} + \delta_{2F\Delta logE_{2(t-1)}} + \\ &\delta_{3F\Delta logCO_{2(t-1)}} + \delta_{4F\Delta logT_{2(t-1)}} + \delta_{5F\Delta = logI_{2(t-1)}} + \varepsilon_{1t}\end{aligned} \tag{8}$$

The Δ symbol represents the first difference operation, while ε 1 represents the residual term. An ARDL bounding testing strategy is used to estimate the long-run relationship between the variables by testing the null hypothesis of no-integration $H0 : \delta 1 = \delta 2 = \delta 3 = \delta 4 = \delta 5$ against alternative null hypothesis $H0 : \delta 1 \neq \delta 2 \neq \delta 3 \neq \delta 4 \neq \delta 5$. Using a critical value with an upper bound of I (1) and a lower bound of I (0), the F-value determines whether or not the null hypothesis of no-integration is rejected. For an inference to be considered conclusive, the computed F-value must fall between predetermined upper and lower bounds. Without knowing the order of integration of underlying variables, such as I (1) or I (0), if this value falls below the lower bound, the conclusion is that there is no co-integration, and if it exceeds the upper bound, the conclusion is that there is co-integration. Upper and lower bound critical values are available in the prior literature [57]. Once co-integration has been established, the next step is to choose the right criteria; in this case, Akaike's Information Criteria (AIC) is the best fit. When the lag length has been determined, the next step is to check for co-integration among variables using the F-statistic. Moreover, Johansen co-integration is used to test the F-statistic reliability. The next step, after co-integration has been confirmed, is to estimate the long run and short run analysis. Three robustness tests—the Reset test, the ARCH test, and the LM test—are used in this research to ensure the model's stability and the validity of the findings for use in policy-making. Model stability for policy recommendation is tested using the CUMUS and CUSUMsq tests.

The time range that is represented by the data used for this analysis is 1980–2019. Previous studies measured CO_2 emission using proxies to determine the relationship between technological innovation and CO_2 emission. The Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, and the US Department of Energy's databases were used to compile the information on CO_2 emissions per capita [58]. Energy consumption in kilogrammes of oil equivalent per person [59,60]. In the current study, trade openness data is measured as a proxy of import + export (percentage of GDP) [46,50]. The number of patents application, both domestically and internationally, was used as a proxy for technological innovation [58] and it is divided by population to get the per capita data of innovation. CO_2 emissions, energy consumption, trade openness, and foreign direct investment (FDI) and innovation figures are drawn from the WDI database.

4. Empirical Results

4.1. Unit root analysis

The goal of this research is to learn more about how India's carbon dioxide emissions are affected by technological innovation. The first premise of the ARDL bound testing procedure is that the variables of interest are not stationary at order 2, i.e., I (2), which would prevent the ARDL technique from being used. The unit root test is a necessary tool when dealing with time series data. Regression analysis results may be spurious if this is not the case. There are two common unit root tests that can be run to determine if the relevant variables are stationary. Tests such as the augmented Dickey-Fuller (ADF) [61] and Phillips–Perron (PP) [62] are used in this research. Although the results in Table 1 suggest that the relevant variables are not stationary at level, the null hypothesis of stationarity cannot be rejected. Based on these findings, the conclusion is that all the series are stationary at first difference, rejecting the null hypothesis of non-stationarity in both the ADF and PP tests. Because all variables are integrated in the first order, the ARDL approach can be taken.

Some tests are necessary for choosing the propoer lag selection criteria, which are then used to estimate the long-run relationship using the bound testing method. In this research, the best lag selection criterion is the Akaike information criterion (AIC). Following [63], the AIC criterion is used to select the shortest possible lag length value while simultaneously minimising the loss of a degree of freedom. In comparison to SBC, which yields more effective and reliable results, the AIC criterion is regarded as superior and effective for capturing dynamic results.

Table 1: *Unit root test*

	Augmented Dickey Fuller		Phillips Pearson		Order of integration
Variables	Level	First difference	Level	First difference	
Log CO_2	0.5481	0.0380**	0.6219	0.0000***	I (1)
Log E	0.9193	0.0001***	1.0000	0.0000***	I (1)
Log I	0.8288	0.0002***	0.8087	0.0002***	I (1)
Log F	0.5920	0.0000***	0.6707	0.0000***	I (1)
Log T	0.9299	0.0000***	0.9321	0.0001***	I (1)

Note: *, ** and *** show the level of significance at 1%, 5% and 10% respectively.
Sources: Calculated by authors.

4.2. Bound testing results

Following the methodology of [64], the next step after determining the appropriate lag length is to investigate the F-value in order to validate the existence of co-integration among variables for the relationship that exists over the long run. The conclusions drawn from the bound F-statistics are presented in Table 2. The findings have shown that the calculated value of the F-statistic is higher than the upper critical boundary at both the 5% and the 10% level of significance, which indicates that the null hypothesis that there is no co-integration should be rejected. The null hypothesis of no co-integration is also tested for other equations, which confirm that long-term relationships between imported technology, energy consumption, and CO_2 emissions are all confirmed to be co-integrated, while the equations for foreign direct investment and trade openness are not.

Table 2: *Results of ARDL bound test*

	Bound testing to co-integration		
Estimated model	Optimal lag length	F-statistics	Remarks
$F_{CO2}/[CO_2/E, F, IT, TO]$	(1,1,0,0,0)	20.19878***	conclusive
$F_{EN}/[E/CO_2, FDI, IT, TO]$	(1,0,0,0,0)	9.740590***	conclusive
$F_{FDI}/[FDI/CO_2, EN, IT, TO]$	(1,0,0,1,0)	2.106738	conclusive
$F_{IT}/[IT/CO_2, FDI, EN, TO]$	(1,0,0,0,0)	3.294555*	conclusive
$F_{TO}/[TO/CO_2, FDI, IT, EN]$	(1,0,0,0,0)	1.727777	non-conclusive
Level of significance	Lower bound I (0)	Upper bound I (1)	
1% Level	3.29	4.37	
5% Level	2.56	3.49	
10% Level	2.2	3.0	

Note: *, ** and *** show the level of significance at 1%, 5% and 10% respectively.
Sources: Calculated by authors.

The results of the F-value test confirm the co-integration of variables. In this study, the robustness of F-statistics is examined using Johansen co-integration [56]. Johansen co-integration has resulted in the production of two statistics: trace statistics and Eigenvalues. At the 5% level of significance, the results of the Johansen maximum Eigen value tests indicate one co-integrated relationship, as shown by [56, 65]. Results point to the validity and efficacy of the conclusions reached using the bound test co-integration method. Table 3 displays the results of the Johansen test.

Table 3: *Results of Johansen co-integration*

	Rank test (trace)		Rank test (maximum Eigenvalue)	
Rank values	Trace statistics	Prob. value	Maximum eigen	Prob. value
r0 =	75.1244	0.0177***	28.1774	0.2054
r1 $\leq$	46.9470	0.0607	19.7482	0.3588
r2 $\leq$	27.1988	0.0969	18.4549	0.1138
r3 $\leq$	8.7439	0.3896	7.3833	0.4448
r4 $\leq$ 1	1.3605	0.2434	1.3607	0.2434

Note: *, ** and *** show the level of significance at 1%, 5% and 10% respectively.
Sources: Calculated by authors.

4.3. Result of tests

After the model has been built and the coefficients estimated, it is crucial to verify their validity and stability. We used the RESET test, the LM test, ARCH test, the R^2 and adjusted R^2 statistics, the F-statistics, and the Durban Watson test to evaluate the overall model fitting. Overall, the model fits the data well if the values of R^2 and adjusted R^2 are close to 1, and if the F-statistics are also significant. Moreover, the Durban-Watson tests show that the model is well-specified. The Breauch-Godfrey LM test was used to identify serial correlation in the estimated model. Breauch-Godfrey LM test's inconclusive findings support the absence of a serial relationship. The normality is confirmed by the null hypothesis results of the Jarque-Bera test. And lastly, a null result for ARCH test is not heteroskedasticity. It is safe to say that the model has sufficient specifications and that the findings can inform policy-making.

Table 4: *Results of diagnostic tests*

	F-statistics	Prob.
X^2 - Reset	0.335587	0.5666
X^2 - ARCH	0.180387	0.6736
LM Test	1.016930	0.2899
R-Square	0.997951	
Adj-R-Square	0.997951	
F-statistics	2597.256 (0.0000)	
Durbin-Watson	2.40	

Note: *, ** and *** show the level of significance at 1%, 5% and 10% respectively.
Sources: Calculated by authors.

4.4. VECM Granger causality approach

Once the long- and short-term estimates have been made, the next step is to determine the direction of causality among variables and to look into the link between the variables by using the cointegration estimation shown in Table 4 [66]. The presence of cointegration between variables permits the determination of the direction of causality. Use the VECM Granger causality approach to determine the direction of causality between innovation technology, energy consumption, foreign direct investment, trade openness, and carbon emissions. VECM is considered the most appropriate method for measuring causality. The following model represents the empirical equation of the Granger causality VECM approach:

$$\begin{aligned}
&\begin{bmatrix} \log C \\ \log E \\ \log F \\ \log I \\ \log T \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} = \begin{bmatrix} \beta_{11k} & \beta_{21k} & \beta_{31k} & \beta_{41k} & \beta_{51k} \\ \beta_{12k} & \beta_{22k} & \beta_{32k} & \beta_{42k} & \beta_{52k} \\ \beta_{13k} & \beta_{23k} & \beta_{33k} & \beta_{43k} & \beta_{53k} \\ \beta_{14k} & \beta_{24k} & \beta_{34k} & \beta_{44k} & \beta_{54k} \\ \beta_{15k} & \beta_{25k} & \beta_{35k} & \beta_{45k} & \beta_{55k} \end{bmatrix} = \\
&\begin{bmatrix} \Delta \log C \\ \Delta \log E \\ \Delta \log F \\ \Delta \log I \\ \Delta \log T \end{bmatrix} = \begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \end{bmatrix} = ect_{it-1} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix}
\end{aligned} \tag{9}$$

Long-run causality is indicated if the (error correction term) ECTt-1 is statistically significant with a negative sign. To determine causality in the short run, we applied the Wald test to the difference and lag difference coefficients of all independent variables and calculated joint short-term and long-term causality. The relationship between energy consumption and carbon emission is shown to be unidirectional in Table 5. Similarly, carbon emissions and technological advancements share a similar connection. Also, FDI has a one–way relationship with trade openness. Joint causality analysis findings support findings from both the long- and short-term causality analyses. Except for energy consumption and trade openness, the results of the causality analysis in this study confirm the existence of long-run causality among variables (Tables 5 and 6).

Table 5: *Results of VECM Granger causality analysis (short run X^2 statistics)*

	Log C	Log E	Log F	Log I	Log T
Log C		4.0522** (0.044)	0.0024 (0.961)	1.053 (0.305)	0.7043 (0.401)
Log E	0.0024 (0.961)		0.0348 (0.852)	1.63E-05 (0.997)	2.3524 (0.125)
Log F	1.3550 (0.244)	0.0174 (0.895)		1.0751 (0.300)	0.0561 (0.812)
Log I	4.1684** (0.041)	0.5510 (0.458)	0.0236 (0.878)		0.3624 (0.547)
Log T	0.1756 (0.675)	0.6061 (0.436)	3.9602** (0.047)	0.4412 (0.507)	

Note: The prob. values are given in square brackets. *, ** and *** show the level of significance at 1%, 5% and 10% respectively.
Sources: Calculated by authors.

Table 6: *Results of VECM Granger causality analysis (long run X^2 statistics)*

	Δ Log C	Δ Log E	Δ Log F	Δ Log I	Δ Log T	ECT(-1)
Δ Log C		-0.67355	-0.000247	-0.023179	0.043077	-0.038189**
prob.		(0.0529)	(0.9611)	(0.3128)	(0.4078)	(0.0475)
Δ Log E	-0.030610		0.003380	0.000349	-0.300743	0.00012
prob.	(0.9610)		(0.8533)	(0.9968)	(0.1352)	(0.9802)
Δ Log F	6.400862	0.148972		0.791489	-0.410818	0.069559**
prob.	(0.2533)	(0.8960)		(0.3078)	(0.8143)	(0.0460)
Δ Log I	2.47541	0.185069	0.005757		-0.230238	-0.481435*
prob.	(0.0498)	(0.4635)	(0.8788)		(0.5516)	(0.0014)
Δ Log T	-0.256834	-0.098121	-0.037680	0.056511		0.52918
prob.	(0.6781)	(0.4421)	(0.0555)	(0.5115)		(0.4315)

Note: The prob. values are given in square brackets. *, ** and *** show the level of significance at 1%, 5% and 10% respectively.
Sources: Calculated by authors.

4.5. Innovative accounting approach

Some researchers have pointed out problems with the VECM-based Granger causality approach [25]. Due to the inability to measure relative strength between variables, the VECM Granger causality approach produces less credible causal relationships. Using the variance decomposition technique, this study investigates the stability of causation in this research. Using a vector autoregressive (VAR) system, this research examines the strength of the connection between India's energy consumption, FDI, trade openness, carbon emissions, and innovation technology by using an innovative accounting approach (IAA). To determine external shocks to each economic variable, the IAA method is effective. The advantage of the IAA approach is that it disregards series integration and the issue of endogeneity. Impulse response function and variance decomposition analysis make up the IAA. It is argued that variance decomposition analysis within the VAR framework provides superior results to other conventional methods [55]. Table 7 displays the outcomes of the variance decomposition method.

Table 7 indicates that 34.58% of carbon emissions are explained by factors external to the scope of this study. The FDI carbon emission share is 0.3%. The contribution of innovation technology is 1.22%, while the contribution of energy consumption and trade openness is approximately 1.38% and 62.5%, respectively, and the highest of all variables. This may explain why only the effect of

Table 7: *Variance decomposition analysis*

Period	S.E.	LNTO	LNC	LNE	LNF	LNI
Variance decomposition of LNTO:						
1	0.082695	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.115830	98.86496	0.045989	0.238398	0.319579	0.531076
3	0.141268	96.85224	0.124014	0.840074	0.673364	1.510312
4	0.163192	94.33195	0.204396	1.826400	0.947341	2.689910
5	0.183394	91.49389	0.265578	3.190769	1.134931	3.914830
6	0.202957	88.43959	0.296383	4.903516	1.254601	5.105914
7	0.222657	85.22963	0.295748	6.916992	1.326050	6.231585
8	0.243114	81.90772	0.270639	9.171028	1.364813	7.285800
9	0.264855	78.51219	0.233029	11.59860	1.382082	8.274103
10	0.288346	75.08055	0.196751	14.13133	1.385652	9.205720
Variance decomposition of LNCO2:						
Period	S.E.	LNTO	LNC	LNE	LNF	LNI
1	0.021453	3.611662	96.38834	0.000000	0.000000	0.000000
2	0.029919	8.063361	90.94018	0.004331	0.100818	0.891311
3	0.036720	14.51614	83.46211	0.007862	0.144019	1.869865
4	0.043016	22.34059	75.12999	0.006163	0.127606	2.395649
5	0.049239	30.69583	66.76360	0.010134	0.097634	2.432795
6	0.055581	38.84050	58.86457	0.048393	0.086810	2.159725
7	0.062136	46.27527	51.67633	0.161473	0.106719	1.780214
8	0.068956	52.74021	45.26457	0.393813	0.155506	1.445899
9	0.076087	58.14762	39.59393	0.787192	0.225877	1.245384
10	0.083581	62.51009	34.58489	1.376425	0.309830	1.218768
Variance decomposition of LNEU:						
Period	S.E.	LNTO	LNC	LNE	LNF	LNI
1	0.084343	4.136589	4.877547	90.98586	0.000000	0.000000
2	0.128477	11.08977	5.872478	80.93539	0.116991	1.985363
3	0.171533	16.65192	6.315754	71.73941	0.313523	4.979393
4	0.215820	20.35236	6.452711	64.71839	0.512900	7.963643
5	0.261762	22.59062	6.446580	59.69985	0.681575	10.58137
6	0.309554	23.83385	6.384365	56.20734	0.812258	12.76219
7	0.359455	24.43601	6.308902	53.80983	0.908508	14.53676
8	0.411814	24.63684	6.240198	52.18177	0.977016	15.96418
9	0.467052	24.59271	6.186765	51.09010	1.024459	17.10597
10	0.525647	24.40424	6.151324	50.37066	1.056472	18.01730

trade openness is detrimental to the environment in India. Similarly, 50.37% of energy consumption is attributable to its shock. The contribution of foreign direct investment, international trade, and innovation technology to energy consumption is 1.06, 24.40, and 18.018 respectively. 6.15% of energy consumption is comprised of CO_2. The proportion of CO_2 and innovation technology in FDI is 1.9% and 12.16%, respectively, while the proportion due to its own shock is 45.23%. The respective percentages of energy and trade are 14.88% and 25.79%. The proportion of FDI

Table 7: *Variance decomposition analysis (cont.)*

Variance decomposition of LNFDI:						
Period	S.E.	LNTO	LNC	LNE	LNF	LNI
1	0.657309	2.650174	1.170094	0.223336	95.95640	0.000000
2	0.771158	6.260955	1.630605	0.648551	88.82238	2.637510
3	0.830587	9.430841	2.037244	1.428859	81.34924	5.753813
4	0.873377	12.01814	2.340266	2.578433	74.94066	8.122499
5	0.910134	14.27502	2.515349	4.068304	69.46917	9.672161
6	0.945906	16.43964	2.561394	5.852739	64.51082	10.63541
7	0.983960	18.65680	2.495925	7.880630	59.73336	11.23329
8	1.026742	20.97944	2.347954	10.09860	54.95222	11.62178
9	1.076223	23.38289	2.150945	12.45169	50.10802	11.90646
10	1.134040	25.78657	1.937271	14.88480	45.23132	12.16003
Variance decomposition of LNIT:						
Period	S.E.	LNTO	LNC	LNE	LNF	LNI
1	0.162557	3.967661	0.144672	1.526500	1.778023	92.58314
2	0.202794	15.07496	0.152220	2.359267	1.731259	80.68230
3	0.229665	27.19797	0.209594	2.803110	1.745055	68.04427
4	0.251894	37.46107	0.337431	2.867149	1.783313	57.55103
5	0.271364	45.27464	0.540980	2.695405	1.824284	49.66469
6	0.288738	51.02159	0.805492	2.432287	1.855129	43.88550
7	0.304531	55.25256	1.103645	2.186546	1.870916	39.58633
8	0.319269	58.41897	1.403875	2.035052	1.871755	36.27035
9	0.333472	60.83443	1.676567	2.033022	1.860004	33.59597
10	0.347643	62.69939	1.897901	2.221731	1.838535	31.34244

Note: Cholesky ordering: LNTO LNCO2 LNEU LNFDI LNIT

caused in innovation technology is 1.83%. CO_2 and innovation technology contribute 1.90% and 31.34% respectively to IT. The proportion of innovation technology's energy consumption is 2.22%, while the proportion of trade openness is 62.70%. CO_2 contributes 0.196751% to trade openness, while energy consumption and innovation technology contribute nominally 14.13% and 9.21%, respectively. The portion attributable to its own shock is 75.08%. 1.38% of trade openness is attributed to FDI. The results of the variance decomposition analysis suggest a causal relationship between innovation technology, energy consumption, foreign direct investment, trade openness, and carbon emission. The results of the VECM Granger causality analysis are reliable and can be used to inform policy.

Turn to the impulse response function, which replaces variance decomposition analysis. The impulse response function describes how independent variables react (Figure 1). The findings of impulse response function indicate that India's carbon emissions are decreasing as a result of increased energy consumption. The forecast error in FDI increases carbon dioxide gas emissions. The reaction of innovation technology to CO_2 emissions increases up to the 5^{th} unit then start to decrease. The predicted inaccuracy for CO_2 emission by trade openness exhibits a rising trend. Due to carbon dioxide, the error in energy consumption forecasts remains constant. The reaction in energy consumption by innovation technology is increasing, while trade openness and FDI are declining at an increasing rate. Furthermore, the effect of carbon emissions on FDI remains

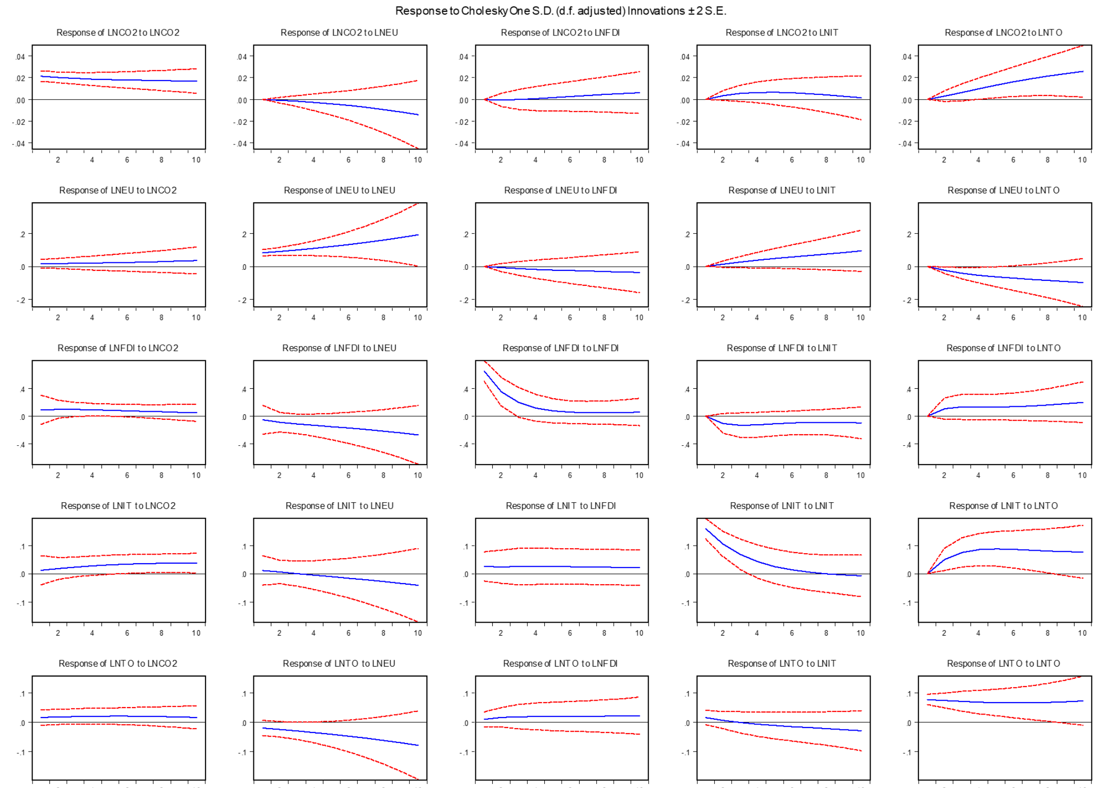

Figure 1: *Impulse response function*

unchanged, whereas the effect of energy consumption decreases across all units. The effect of innovation technology on FDI decreases up to the third unit then remains constant. In contrast, the impact of trade openness increases up to the third unit and then becomes stable.

Moreover, In the case of innovative technology, carbon emission response increases up to the fifth unit and then becomes uniform throughout the remaining units, whereas it decreases at an increasing rate in response to energy consumption. In contrast, FDI has no effect on technological innovation. Initially, the impact of trade openness on innovation technology is increasing and subsequently it levels off. The response of innovation technology to trade openness is favorable up to the third point, after which it began to fall. Energy usage declines at a decreasing pace in reaction to trade openness, whereas FDI remains unaffected. Predictions of trade openness based on carbon emissions continue to be constant.

5. Conclusion

The current study incorporates energy consumption, FDI, and trade openness to analyse the relationship between innovation technology and carbon dioxide emissions from 1980 to 2019. The long-run connection between exogenous and endogenous variables is identified using the ARDL cointegration method. In order to find causal relationships between variables, both long- and short-term, the VECM Granger causality technique is used. The ARDL bound testing method is used once the time series' features have been examined. Diagnostic tests are then used to validate findings prior to policy implementation. The validity of the VECM Granger causality test is evaluated with the use of an innovative accounting method (IAA).

Some of the relationships and interconnections found in this empirical analysis are remarkable. To summerise the findings, the import of innovation technology is a long-term and short-term contributor to carbon emissions in India. Second, while the use of energy does have an immediate impact on CO_2 emissions, it has no negative effects on the environment in the long run. Third, there is no context provided for India's carbon emissions in terms of how trade openness affects CO_2 emissions either in the long or short term. Foreign direct investment (FDI) has the opposite effect in India; in the short term, it does not contribute to environmental deterioration, while in the long term, it has a major impact on carbon emissions. Finally, a short-term study using VECM Granger causality verifies the one-way causation between energy use and carbon emissions, and a similar relationship between technological innovation and carbon dioxide emissions. Furthermore, foreign direct investment is correlated with trade openness in only one direction.

The study's empirical findings are very interesting. The findings support the idea that India's carbon emissions are exacerbated by innovation technology. This means that the latest innovation technology is not being transferred to India through FDI and commerce. When it comes to cutting back on carbon emissions, cutting-edge technology is crucial. Nonetheless, it may not always be the case that advances in technology lead to lower energy use and fewer greenhouse gas emissions4. India is still working hard to get to the point where it can utilise cleaner technology, yet the majority of the technology used in manufacturing now is antiquated and inefficient. The study's results highlight the importance of importing technology to the attention of policymakers, who should develop policy to limit the import of obsolete and carbon-intensive technology by applying dumping tariffs. Emission-focused manufacturing should be subject to strict carbon pricing regulations. Regarding production and efficiency, global businesses need to catch up to their domestic counterparts by adopting cutting-edge processes and technology beneficial in terms of reducing air pollution.

Second, empirical studies demonstrate that energy use is the primary source of CO_2 emissions in the environment. According to the data, India's long-term and short-term per capita CO_2 emissions are unaffected by energy use. It attracts the attention of policymakers to the issue of unproductive energy consumption. This investigation yields various long-term and short-term findings. The differing effects for the short-term and long-term motivate politicians to establish distinct short-term and long-term programmes, such as vision 2025 and vision 2050. In light of the empirical examination, this study's findings are generally consistent with the current literature and provide solid support for policy application. To attain sustainable development objectives, the Indian government should implement productive energy consumption and trade policies.

Declaration of interest: None

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