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An Empirical Analysis of Economic Growth, FDI, Renewable Energy Consumption and Trade Openness on Greenhouse gas emissions in India

Ashish Narayan Jha[1], Dr. Rakesh Kumar Srivastava[2]
[1]Ph.d (Research Scholar), School of Management, Gautam Buddha University
[2]Assistant Professor (Research Guide), School of Management, Gautam Buddha University

ABSTRACT

This study examines the complex relationship between greenhouse gas emissions and four key macroeconomic variables (economic growth, foreign direct investment (FDI), renewable energy consumption, and trade openness) in the Indian context over the period 2000 to 2021. Using the Autoregressive Distributed Lag (ARDL) bounds testing approach, the analysis uncovers a long-run equilibrium relationship among the variables. The analysis revealed a U-shaped link between GDP and emissions, indicating that while emissions tend to fall at lower income levels, they rise again once a certain income threshold is crossed thereby challenging the conventional EKC hypothesis. While FDI was found to have no notable impact on emissions, increased consumption of renewable energy significantly reduced emissions in both the short and long term, emphasizing its environmental value. Conversely, greater trade openness was linked with higher emissions over time, suggesting that increased integration with global markets may come at an environmental cost. These insights point to the importance of pursuing clean energy strategies and sustainable trade practices as India continues to grow economically.

Keywords: *FDI, Economic growth, Renewable energy consumption, Carbon emission, ARDL*
JEL codes: *Q56, F64, O44, Q43, F21*

1. INTRODUCTION

India, recognized as one of the most rapidly advancing developing nations, has experienced a remarkable transformation over the last 20 years. This period has been marked by consistent economic expansion, increased foreign capital inflows, and deeper integration into the global trade. According to the World Bank (2025), India's GDP per capita has more than tripled since 2000, while its integration with global markets through trade and investment has significantly intensified. However, this rapid development has coincided with a substantial increase in greenhouse gas emissions, positioning India as world's third-largest emitter of carbon dioxide (CO_2) from fuel combustion (International Energy Agency, n.d.).

Understanding how economics and globalization influence environmental outcome is vital to current sustainable development discourse. India has pledged to reduce the emission intensity of its GDP by 45% from 2005 levels by 2030 and to achieve about 50% cumulative electric power installed capacity from non-fossil fuel-based energy resources by 2030 (Government of India, 2022). India has also committed to achieving net-zero carbon emissions by 2070. These goals align with Sustainable Development Goal 7, which calls for the extensive use of clean energy, and SDG 13, which advocates for decisive measures to address climate issue. Hence, analyzing the environmental impact of economic expansion, investment, and trade liberalization becomes crucial for harmonizing development strategies with global climate goals.

There are conflicting perspectives and empirical results regarding the environmental impact of foreign direct investment (FDI) on a country, leading to two conflicting views: the Pollution haven Hypothesis (PHH) and the Pollution Halo Hypothesis (PH) (Demena and Afesorgbor 2020). As noted by Cole (2004), firms in countries with strict environmental regulations often shift operations to nations with weaker standards, resulting in higher pollution levels in host countries thus creating so-called "pollution havens. Contrary to this view, FDI can improve environmental outcomes by introducing cleaner technologies to developing economies (Atici, 2012). According to this view FDI can promote environmental sustainability by mitigating carbon emissions rather than hinder it. However, empirical research has provided mixed evidence. Studies conducted by Tariq et al. (2022), Hoa et al. (2023), and Effendi et

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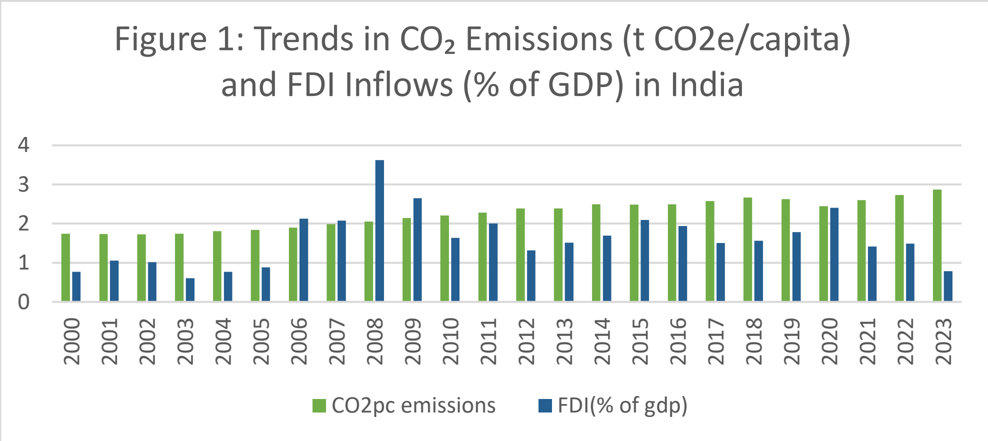
al. (2024) failed to reject the PHH whereas studies by Hao et al. (2020), Qamri et al. (2022), and Rafique et al. (2020) rejected the PHH and found support for Pollution Halo (PH).

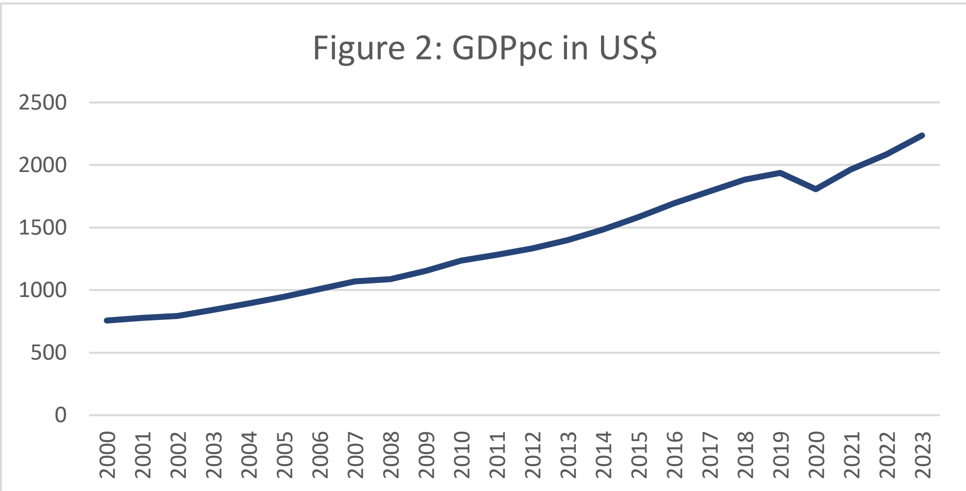
As shown in Figure 1, both Foreign Direct Investment (% of GDP) and average amount of greenhouse gases emitted per person in India have shown generally an upward trend in last 20 years. So, at this point of time, the nexus between FDI and greenhouse gas emissions should be re-assessed, specifically in Indian context.



Source: World Development Indicators, The World Bank

Similarly, trade openness can exert both positive and negative effects on emissions depending on the scale, composition, and technique effects (Grossman & Krueger, 1995). Zameer et al. (2020), Rana and Sharma (2023) reported the damaging influence of Trade openness on Environmental quality. On another hand Lv ad Xu (2019) found trade to be negatively impacting Carbon emissions.

Moreover, Economic growth is often found to have a non-linear relationship with environmental degradation, as suggested by the Environmental Kuznets Curve (EKC) hypothesis (Grossman & Krueger, 1991). At lower income levels, economic growth tends to increase emissions, but beyond a certain threshold, higher income levels lead to greater demand for environmental protection and cleaner technologies (Dinda, 2004). Over the years many scholars have investigated EKC hypothesis. Naz et al. (2019), Tarique et al. (2022) and Effendi et al. (2024) refuted the EKC hypothesis whereas Isik et. al (2019) found support for the EKC hypothesis in 14 states of USA. As shown in Figure 1 and Figure 2 Carbon emission and GDP per capita has been in constant rising trend.



Source: World Development Indicators, The World Bank

In recent years, rising the renewable energy share in total energy mix has emerged as a key strategy to resolve carbon emissions issue (Shahbaz & Balsalobre-Lorente, 2020). In line with this, India also substantially raised investment in renewable energy sources. India's total installed renewable energy (RE) capacity has risen to 220.10 GW, marking an increase from 198.75 GW in the previous fiscal year, driven by a record annual addition of 29.52 GW (Ministry of New and Renewable Energy, 2025). The role of Renewables in curbing carbon emission is also supported by many scholars (Raihan et al., 2025; Tariq et al., 2022; Osei, 2025).

Although extensive studies exist on the link between growth and the environment, and also the role of FDI, trade liberalization, and renewable energy adoption on emissions, there is still a need for integrated research combining all these variables in a unified framework. As far as we are aware, no previous research has jointly examined the impact of these variables on greenhouse gas emissions in India over the time period 2000– 2021. This study addresses the gap by employing ARDL model developed by Pesaran, Shin, and Smith (2001) to empirically examine how these macroeconomic variables influence emissions in India, offering a long-run, evidence-based foundation for sustainable policy formulation.

2. LITERATURE REVIEW

We organize our review of existing research into four main areas reflecting the key themes of our study:

2.1 FDI and Emissions

A large volume of existing research has explored how FDI affects environmental outcomes, presenting mixed findings. Some studies support the Pollution Haven Hypothesis (PHH), while others find evidence for the Pollution Halo Hypothesis (PH) (Luo et al., 2022).

Internationally, Nawaz et al. (2024) employed ARDL and found FDI to have an insignificant positive effect on CO_2 emissions in Italy, while Raihan (2024) highlighted that FDI significantly contributes to economic growth in Vietnam, indirectly linking it to emissions. Using Robust least square regression technique, Naz et al. (2019), in a study on Pakistan, identified a significant positive association between FDI and CO_2 emissions, supporting the PHH, whereas Hao et al. (2020) provided contrary evidence from China, showing that FDI reduces environmental pollution, aligning with the PH. Similarly, Osei (2025) noted that while FDI inflows increase CO_2 emissions, renewable energy moderates this impact in Sub Saharan African countries. In the case of south Asian economies, Tariq et. al (2022) found FDI to be negatively influencing CO_2 emissions while Qamri et al. (2022) reported FDI negatively affects environment via financial development. Mukhtarov et al. (2021) highlighted that in Azerbaijan, the environmental impact of FDI is sector-specific and time-varying. In the context of G8 countries, Abid et al. (2022) reported the significance of FDI in reducing carbon emissions. Rafique et al. (2020) also found the support for Pollution halo hypothesis in the context of BRICS economy.

In the Indian context, Zameer et al. (2020) utilized ARDL model and found support for PH and reported that FDI, along with innovation, contributes to lowering CO_2 emissions. Contrary to this, Rana and Sharma (2023) reported that damaging impact of FDI on CO_2 emissions in India. Holtbrügge and Raghavan (2025) echoed similar concerns, identifying that certain types of FDI tend to exacerbate emissions, particularly in pollution-intensive sectors. Derindag et al. (2023) used panel threshold regression and examined the impact of FDI and trade openness on carbon emission in 20 Indian industrial sectors. They identified nonlinear effects, FDI initially found to be reducing emissions and increased them at higher intensities.

2.2 Trade and Emissions

Foreign trade is often examined in relation to environmental degradation. In their study covering the period from 1990-2020, Effendi et. al (2024) and Ertugrul et al. (2016) observed that trade openness positively influences carbon emissions only in the long run. Xuan (2025) found that trade openness initially contributes to an increase in emissions but subsequently facilitates a decline in emissions over time. On the other hand, Ling et al. (2015), using ARDL bound testing approach for Malayasia, found that trade openness negatively affects carbon emissions. Lv and Xu (2019) found that trade openness negatively influences carbon emissions in the short run, whereas a significant positive effect was observed in the long run.

Rafique et al. (2020) reported a significant positive relationship between trade openness and carbon emissions in BRICS nations, suggesting that increased trade activity may heighten industrial output and environmental pressure in the absence of strong regulatory frameworks. Zameer et al. (2020) reported the statistically significant role of trade openness in driving CO_2 emissions In India. While Ohlan (2015) reported the insignificant effect of Trade openness on Carbon emission in short run and long run.

2.3 Economic Growth and Emissions

When it comes to economic growth which is often proxied by Gross Domestic Product (GDP), India is set to become the fourth-largest economy in the world by the end of 2025 (International Monetary Fund, 2025). However, on the other hand, India's emission intensity is also rising rapidly. This indicates that while the country is experiencing significant economic growth, it is coming at the cost of environmental sustainability (Balsalobre-Lorente et al., 2018; Zameer et al., 2020)

In the global context, the empirical evidence on the relationship between economic growth and carbon emissions remains far from conclusive. For instance, Naz et al. (2019) rejected the Environmental Kuznets Curve (EKC) hypothesis in Pakistan, they found that both GDP per capita and its squared term were positively associated with CO_2 emissions. Similarly, Adedoyin et al. (2022), using a two-step System GMM approach across Sub-Saharan African countries (2002–2014), reported a strong positive link between economic growth and emissions, suggesting that the region's growth is still largely tied to pollution-intensive sectors. Nawaz et al. (2024), by contrast, found an insignificant relationship in Italy, while Ren et al. (2021) identified a bidirectional causality between growth and emissions in the Chinese steel industry. However, Ling et. al (2015) found support for EKC hypothesis in Malaysian economy and Isik et. al (2019) also supported the EKC hypothesis in some states of USA.

Employing ARDL model, Zameer et al. (2020) reported that GDP growth significantly increased carbon emissions. Similarly, Rana and Sharma (2023) observed a positive relationship between GDP and CO_2 emissions. In contrast, Uche et al. (2023) critically reassessed the Environmental Kuznets Curve (EKC) hypothesis in the Indian context using the novel Nonlinear ARDL (NARDL) approach over the period 1980–2018.Uche et al. (2023) and Ohlan (2015) supported the existence of EKC in Indian economy. studies conducted to explore this relationship have provided mix results. Some found support for the EKC and some refuted the EKC.

2.4 Renewable Energy and Emissions

In the global context, Naz et al. (2019), using the GMM technique, found that renewable energy contributes to the mitigation of carbon emissions in Pakistan. Similarly, Hoa et. al (2023) reported that renewable energy significantly reduces Carbon emissions in Vietnam. Osei (2025) demonstrated the moderating role of renewable energy consumption in reducing the environmental impact of FDI in Sub-Saharan African countries (SSA). Adedoyin et al. (2022) reported similar findings for SSA, observing that renewable energy consumption exerts a negative influence on carbon emissions. Tariq et al. (2022) utilized DOLS and FMOLS technique and reported the significance of renewable energy in mitigating carbon emission in south Asian economy. Ping and Shah (2023) further noted that REC significantly reduces emissions in both the short and long run, especially when coupled with higher education in BRICS economy.

In the Indian context, Zameer et al. (2020) employed ARDL model to investigate the impact of renewable energy consumption along with other macroeconomic variable on Carbon emission and reported the critical role played by renewable energy consumption in reducing CO_2 emissions. Their findings supported broader global evidence on the environmental benefits of transitioning to renewable sources. Sahoo and Sahoo (2022) employed the ARDL bounds testing approach and the Toda–Yamamoto Granger causality test to study the dynamics between Renewable energy consumption, Non-renewable energy consumption and Carbon emissions in India. They observed that renewable energy (excluding hydropower) reduces Co_2 in India.

2.5 Outcome of the Literature Review

Overall, existing literature underscores a complex and context-specific interplay among growth, foreign investment and trade in shaping environmental outcomes. While FDI, trade and economic growth can exacerbate and mitigate greenhouse gas emissions depending on sectoral and institutional factors, renewable energy consistently emerges as a crucial tool for environmental sustainability. For India, the dual forces of liberalization and development necessitate a balanced strategy that attracts clean FDI, promotes green energy adoption, and ensures sustainable growth.

3. METHODOLOGY

we have presented the variables and the methodological framework used in following subsections:

3.1 Data

This study seeks to re-examine whether India's economic growth represents clean growth in terms of environmental quality or constitutes dirty growth. In addition, it seeks to investigate the EKC, PHH, and PH phenomenon within India over the period 2000–2021. To achieve this, we used a range of variables and the details along with the source of each is provided in table 1.

Table 1: List of Variables

Variable	Type	Proxy	Source	Supporting Literature
Greenhouse gas (Co_2)	Dependent	Per capita carbon dioxide emission in tonnes (excluding LULUCF)	WDI, World Bank (2025)	Nawaz et al, 2024; Blanco et al, 2013
Growth (GDP)	Independent	GDP_{pc} (constant 2015 US dollar)	WDI, World Bank (2025)	Zameer et al, 2020; Kaushal et al, 2024
Investment (FDI)	Independent	FDI, Net inflows (% of GDP)	WDI, World Bank (2025)	Rana & Sharma, 2019; Luo et al, 2022
Renewable Energy (REC)	Independent	Renewable energy consumption (% of total final energy consumption)	WDI, World Bank (2025)	Adedoyin et al, 2022; Ali et al, 2025
Trade Openness	Independent	Trade (%of GDP)	World Bank (2025)	Adam & Amoah, 2025; Samour et al, 2022

Source: Author's own work

Each variable was expressed in natural logarithmic terms to stabilize variance across observations and to facilitate elasticity-based interpretation of the model coefficients.

3.2 Stationarity Tests

To apply the ARDL model appropriately, it is essential that the variables be stationary either at level, at first difference, or a mix of both; however, none of the variables should exhibit stationarity at the second difference (Chen et al., 2024). To ensure that none of the variables are integrated of order two, we employed the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) and the Phillips-Perron (PP) test (Phillips & Perron, 1988) to examine the stationarity and order of integration of each time series variable.

3.3 Econometric Model

After the estimation of the stationarity and the order of integration, we employed ARDL bounds testing method for cointegration to examine whether a long-run relationship exists among the variables (Pesaran, Shin, & Smith, 2001).

The standard ARDL model is presented as:

$$\begin{aligned}\Delta(LnCO2_t) = \gamma_0 &+ \sum_{k=1}^{\rho} \beta_{1k}\ \Delta LnCO2_{t-k} \\ &+ \sum_{k=0}^{\rho} \beta_{2k}\ \Delta LnGDP_{t-k} \\ &+ \sum_{k=0}^{\rho} \beta_{3k}\ \Delta LnGDPSQ_t \\ &+ \sum_{k=0}^{\rho} \beta_{4k}\ \Delta LnFDI_t \\ &+ \sum_{k=0}^{\rho} \beta_{5k}\Delta REC_t \\ &+ \sum_{k=0}^{\rho} \beta_{6k}\Delta TO_t + \theta_1 LnCO2_{t-1} \\ &+ \theta_2 LnGDP_{t-1} \\ &+ \theta_3 LnGDPSQ_{t-1} \\ &+ \theta_4 LnFDI_{t-1} + \theta_5 REC_{t-1} \\ &+ \theta_6 TO_{t-1} + \varepsilon_t\end{aligned}$$

In above equation, Δ denotes the first-difference transformation, while the summation symbol (Σ) denotes the total across selected lags for each variable. Coefficients β_1 to β_6 capture the short-run impacts of the explanatory variables. Coefficients θ_1 to θ_6 represent the long-term associations with the dependent variables. The term ε_t refers to the random error component.

ARDL bounds testing method by Pesaran et al. (2001) is not suitable for studies having small sample size (Ahmad et al., 2017; Zameer et al., 2020) and Narayan (2005) method for cointegration analysis is suitable for 30 or more than 30 observations. Since the study uses annual data over a period of 21 years, the sample size falls below the threshold of 30 observations for which Narayan (2005) provides critical value bounds. In the absence of published critical values for samples less than 30, we employed the closest available Narayan bounds (for T = 30) as a reference point, following precedent in existing small-sample ARDL applications (Koondhar et al., 2020). While this is a limitation, we address it by conducting several post-estimation diagnostic tests such as Breusch-Godfrey Serial Correlation LM (Breusch, 1978; Godfrey, 1978) test, Breusch-Pagan-Godfrey (Breusch & Pagan, 1979; Godfrey, 1978) heteroscedasticity test, Jarque-Bera (Jarque & Bera, 1980) normality test, Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests (Brown, Durbin, and Evans (1975). If the F-statistics of the bounds test is more than the upper critical value bounds (Narayan, 2005) then it is the indication of long run cointegration among the variables (Raihan et., al 2024). Further, the Error Correction Model (ECM) is employed to analyze short-run fluctuations and to determine the rate at which the system adjusts back to long-run equilibrium following a disturbance (Pesaran et al. (2001). A negative and statistically significant error correction term confirms the presence of a stable long-run equilibrium and indicates the rate at which deviations from the long-run path are corrected (Nkoro & Uko, 2016).

A key advantage of using the ARDL approach over alternative models is its ability to simultaneously estimate both short-run adjustments and long-run equilibrium relationships within a single unified equation, making it suitable even for smaller sample sizes (Pesaran et al. 2001). Since ARDL relies on the VAR framework, we selected the appropriate lag length using the Akaike Information Criterion (AIC) (Prakash & Sethi, 2023). As it is especially effective in contexts involving limited data points

3.4 Multicollinearity Diagnosis and Resolution

High correlation was observed between some pair of explanatory variables (Table 3) which indicated the potential multicollinearity issue. To further confirm the multicollinearity issue we applied Variance inflation factor. To resolve this issue, an orthogonalization approach was applied (García, Salmerón, García, & García, 2020). The renewable energy consumption was regressed on GDP per capita, and the residuals were used as an orthogonal component to eliminate collinearity while retaining both variables in the regression model (Wurm & Fisicaro, 2014). Additionally, we further investigated whether economic growth exhibits a nonlinear influence. For this purpose, a squared value of the logarithm of GDP was introduced in the equation. To address the potential multicollinearity between the original and squared terms, mean-centering was applied (Aiken & West, 1991)

4. RESULTS AND DISCUSSION

This section outlines the main empirical outcomes of this study. We begin by conducting initial diagnostic checks, then proceed with the stationarity analysis, apply the ARDL bounds testing approach (Narayan, 2005) and calculated both the short-run and long-run relationships, followed by diagnostic tests for model robustness.

4.1 Descriptive Statistics and Multicollinearity Analysis

The means and standard deviations indicated moderate level of variation across the dataset. However, the skewness and kurtosis statistics fell within acceptable thresholds, implying that the data distribution approximated normality. Additionally, the normality was also supported by the J-B test, as all of the variables showed insignificant deviation from normality at the 5% level (Table 2).

Table 2: Descriptive

Statistic	$LnCo_2$	LnFDI	LnGDP	LnREC	LnTO
Mean	0.775320	0.414324	7.126358	3.642029	3.72865
Median	0.808304	0.467602	7.137414	3.587676	3.7565578

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Maximum	0.979767	1.286619	7.583405	3.852273	4.021661
Minimum	0.547115	-0.501060	6.628972	3.48124	3.257821
Standard Deviation	0.157576	0.445505	0.319928	0.134368	0.222587
Skewness	-0.26281	-0.319977	-0.068665	0.395386	-0.729699
Kurtosis	1.506474	2.569489	1.695923	1.528451	2.705382
Jarque-Bera (J-B)	2.297988	0.545307	1.576186	2.558212	2.03192
Probability (P)	0.316955	0.761357	0.454711	0.278286	0.362055
Observations	22	22	22	22	22

Source: Author's own work

After determining the descriptives we assessed the linear association among the variables for this purpose the correlation coefficients (Pearson, 1895) and the Variance Inflation Factor (VIF) (O'Brien, 2007) for the log transformed series is computed (see Table 3 and 4). The dependent variable $LnCo_2$ exhibited strong correlation with LnGDP and LnREC. This indicated that both variables have high explanatory power for CO2 emissions in the model. However, due to the high correlation between LnGDP and LnREC, there may be a concern for multicollinearity. This was further examined through the VIF method (Table 4). The VIF (pre-orthogonalization) values for LnFDI and LnREC were within the acceptable threshold while, LnREC exceeded the standard acceptable limit of 10, indicating the presence of severe multicollinearity with other variables.

Table 3: Correlation Matrix

	$LnCo_2$	LnFDI	LnGDP	LnREC	LnTO
$LnCo_2$	1				
LnFDI	0.531966	1			
LnGDP	0.979165	0.513547	1		
LnREC	-0.97987	-0.56438	-0.93547	1	
LnTO	0.568822	0.62371	0.49661	-0.63052	1

Source: Author's own work

Table 4: VIF

Variable	VIF (pre-orthogonalization)	VIF (post-orthogonalization)
LnFDI	1.799281	1.799281
LnGDP	9.158938	1.597886
LnREC	11.32011	1.413762
LnTO	2.295136	2.295136

Source: Author's own work

We applied orthogonalization technique for mitigating multicollinearity and ensuring the reliability of our model. It is a widely recommended econometric technique in situations where explanatory variables are highly correlated (García, Salmerón, García, & García, 2020). It helps isolate the distinct explanatory power of a variable by removing the shared variance with another highly collinear predictor. Multicollinearity inflates the standard errors of regression coefficients and undermines the precision of estimated effects, making it difficult to isolate the independent influence of variables (Gujarati & Porter, 2009). In response to this, we employed the orthogonalization technique to resolve the issue between LnGDP and LnREC.

To eliminate the collinearity between GDP and renewable energy consumption, we regressed LnREC on LnGDP

$$LnREC_t = \propto + \beta LnGDP_t + \varepsilon_t$$

This step identified the component of LnREC that is linearly dependent on LnGDP. The residuals from the above regression capture the variation in renewable energy consumption that is independent of lnGDP. These residuals are, by construction, uncorrelated with LnGDP, thus removing the source of multicollinearity.

The orthogonalized variable was then used in place of LnREC in the model. This allowed us to assess the independent effect of LnREC on $LnCo_2$, net of GDP influences. After the application of orthogonalization technique, we rechecked the VIF values and as expected the VIF (post-orthogonalization) value for all the variables fall within the acceptable limit.

4.2 Stationarity Test

We applied the ADF and PP tests for determining the stationary properties of the variables (Dickey & Fuller, 1979; Phillips & Perron, 1988). The initial test results revealed that the variables were not stationary in their level form, as indicated by p-values exceeding the 0.05 threshold. However, after converting the data to first differences, all variables exhibited stationarity, with test statistics showing significance. This outcome confirmed that the series are integrated of order one, validating the appropriateness of using the ARDL bounds testing methodology for exploring long-run associations among the variables (Pesaran et al. 2001).

Table 5: Unit Root Test

Variable	Augmented Dickey Fuller Test (ADF)		Phillips-Perron Test (PP)	
	At levels	At first difference	At levels	At first Difference
$LnCo_2$	2.703592 (0.9970)	-2.809452*** (0.0075)	2.703592 (0.9970)	-2.809452*** (0.0075)
LnFDI	2.703592 (0.9970)	-2.809452*** (0.0075)	-1.308075 (0.1703)	-4.84895*** (0.0001)
LnGDP	6.503972 (1.0000)	-4.386325*** (0.0029)	6.905190 (1.0000)	-4.380354*** (0.0030)
LnREC	-1.494713 (.1230)	-2.730904*** (0.0090)	-0.858258 (0.3322)	-2.720368*** (0.0092)
LnTO	0.975959 (0.9066)	-3.429989*** (0.0017)	0.923363 (0.8986)	-3.432620*** (0.0016)

*** indicates significance at 1% level, P-values ( )

Source: Author's own work

4.3 Model Lag structure selection

Before estimating the ARDL model we employed the Akaike Information criterion (AIC) which is particularly suitable for small samples (Pesaran & Shin, 1999). Among the evaluated lag combinations, the ARDL (1,0,0,0,0,1) model had the lowest AIC value of -5.98, compared to alternative specifications (e.g., ARDL (1,0,0,0,0,0) with AIC -5.64). Hence, we selected the model with 1 lag in Dependent variable and 1 lag in LnTO and zero lag in other independent variables. The choice of fewer lags for the independent variables also ensures model parsimony and avoids overfitting, which is particularly important when working with small time-series samples (Pesaran et al., 2001).

4.4 ARDL Bounds Test for Cointegration

As presented in Table 6, the F-statistic was substantially higher than the upper critical bounds suggested by Narayan (2005) at the 1%, 5%, and 10% significance levels. Therefore, we rejected the null hypothesis of no cointegrating relationship among the variables and the outcomes affirmed the significant long-term association among the variables (Narayan, 2005). These results also supported the suitability of ARDL modelling framework for further analysis.

Table 6: Bounds Test for Cointegration

Statistics	**Value**	**K**
F	23.8836	5
Critical value bounds		
Significance level	**I(0)**	**I(1)**
10%	2.407	3.517
5%	2.910	4.193
1%	4.134	5.761

Source: Author's own work

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4.5 ARDL Long -run and Short-run dynamics

As illustrated in Table 7, this study evaluated the long-run and short-run coefficients along with the error correction term (Pesaran, Shin, & Smith, 2001). Economic Growth (LnGDP) was found to have a positive and statistically significant impact in both time periods. Specifically, in the long run, a 1% rise in GDP per capita correspond to an approximate 0.42% rise in per capita carbon emissions, while the short run effect was 0.36%. Similarly, the squared GDP term (LnGDPSQ) term also showed a statistically significant and positive effect in both the long run (0.41%) and the short run (0.36%), suggesting that the income-emission relationship is U-shaped and thus does not align with the EKC hypothesis in the Indian context. These results are consistent with earlier research (Naz et al, 2019; Hoa et al, 2023; Mukhtarov et al, 2021; Adedoyin et al, 2022; Abid et al, 2022; Rafique et al, 2020; Xuan, 2025; Zameer et al, 2020; Rana & Sharma, 2023). In contrast, FDI exhibited a negative but statistically insignificant influence on carbon emissions during both periods. However, renewable energy consumption significantly reduced carbon emissions in both time period. A 1% rise in REC resulted in the reduction of 0.54% per capita carbon emissions in the short run and 0.62% in the long run. These findings were in line with the outcomes of Naz et al. (2019), Tariq et al. (2022), Hoa et al. (2023), Ping and Shah Osei (2025), Xuan (2025), and Zameer et al. (2020). Trade openness had a positive influence on emissions in both time frames. In the long run, a 1% rise in trade openness resulted in a 0.19% rise in carbon emissions. In the short-run, the immediate impact was insignificant but it's lagged impact was both positive and statistically significant, indicating a delayed contribution of trade activities to environmental degradation. Our finding for trade openness and carbon emissions resonate with those of Zameer et al. (2020), Rafique et al. (2020), Effendi et al. (2024), and Rana and Sharma (2023) they similarly noted that greater trade openness can intensify CO_2 emissions, particularly in developing nations. Together, these studies highlighted a shared concern: that without adequate environmental safeguards, the gains from economic growth and expanding trade may come at the cost of environmental sustainability.

The negative and statistically significant error correction term suggested the existence of a long-run equilibrium relationship, with approximately 87% of deviations corrected within a single period (Pesaran, Shin, & Smith, 2001). Overall, the model demonstrated a strong fit with an R^2 of 0.9969, validating the robustness of the estimated relationships.

Table 7: Long-run and Short-run estimation

Variables	Long-run			Short-run		
	Coefficient	t-statistic	p-value	coefficient	t-statistic	p-value
LnGDP	0.42098***	19.41321	0.0000	0.365441***	6.830066	0.0000
LnGDPSQ	0.413951***	8.093259	0.0051	0.359304***	3.475119	0.0041
LnFDI	-0.008857	-0.992878	0.3389	-0.007688	-1.008147	0.0041
LnREC	-0.624626***	-7.392773	0.0000	-0.542216***	-6.305857	0.0000
LnTrade	0.193474***	3.65014	0.0029	0.058514	1.776649	0.0990
LnTrade (-1)				0.167908***	4.070767	0.0013
C	-2.977332***	-28.59266	0.0000	-2.584541***	-8.827326	0.0000
ECT (-1)				-0.868073***	-8.172643	0.0000
R^2: 0.9969		**Adjusted R^2: 0.9952**				

***indicates significance at 1% level

Source: Author's own work

4.6 Diagnostic Tests for ARDL Model

The results for the various tests ensuring the robustness and reliability of the model have been provided in Table 8. The Breusch-Godfrey Serial Correlation LM test indicated no presence of serial correlation, as the probability values for the F-statistic (0.1521) was greater than the 5% significance level (Breusch, 1978; Godfrey, 1978). Similarly, the Breusch-Pagan-Godfrey heteroskedasticity test revealed no evidence of heteroskedasticity in the residuals (Breusch & Pagan, 1979; Godfrey, 1978). The Jarque-Bara normality test also indicated the normality of the residuals ((Jarque & Bera, 1980). Furthermore, the

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Ramsey RESET test confirmed that the model was correctly specified, as indicated by a very high p-value of 0.9837, suggesting the absence of omitted variable bias (Ramsey, 1969). Lastly, the CUSUM and CUSUM of Squares plots showed that the recursive residuals remained within the 5% significance bounds throughout the sample period, thereby confirming the structural stability of the model parameters over time (Brown, Durbin, and Evans (1975). Overall, these diagnostic tests validate the reliability and consistency of the ARDL model used in the analysis.

Table 8: Diagnostic Tests

Diagnostic	**Null Hypothesis (H_0)**	**Test Statistic**	**probability**	**Decision**	**Implication**
Breush-Godfrey Serial correlation LM	No presence of serial Correlation at lag 1	F-stat=2.3388	0.1521	Fail to reject H_0	No autocorrelation
Breush-Pagan-Godfrey Heteroscedasticity	Homoscedastic residuals	F-stat= 1.4339	0.2725	Fail to reject H_0	No Heteroscedastic
Normality test	Residuals are Normally distributed	Jarque-Bera=0.239374	0.887198	Fail to reject H_0	Residuals exhibit normality
Ramsey RESET Test	Functional form of the model is correct	F-stat=0.000437 Likelihood ratio= 0.000764	0.9837 0.9779	Fail to reject H_0	No misspecification
CUSUM Stabilty Test	Parameters are stable over time			Within 5% bounds	Stable
CUSUMSQ Stability Test	Variance of Parameter is stable overtime			Within 5% bounds	Stable

Source: Author's own work

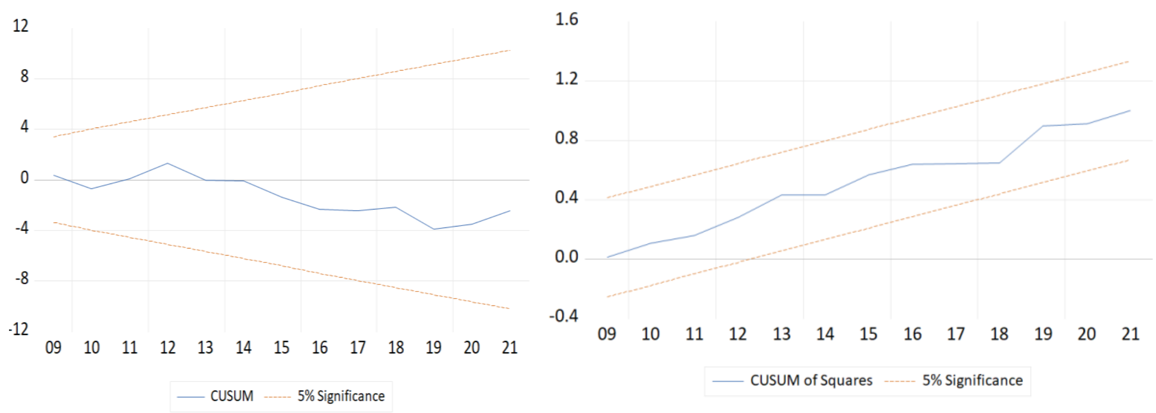

Figure 3: CUSUM and CUSUMSQ

5. CONCLUSION

This study investigated the long- and short-run relationships between greenhouse gas emissions and key macroeconomic indicators in India over the period 2000 to 2021. The application of the ARDL bounds testing approach (Narayan, 2005) confirmed a long-run cointegrating relationship among the variables. The results revealed that both GDP and its squared term are significantly and positively related to emissions, supporting a U-shaped pattern. This outcome contradicts the Environmental Kuznets Curve (EKC) hypothesis, which typically forecasts an inverted U-shape, and instead reflects a scenario where rising income levels in India have been linked to increased emissions. FDI was found to have no statistically significant impact on emissions in either the long or short term, suggesting a neutral environmental role for foreign investments during the study period. In contrast, renewable energy consumption significantly reduced emissions across both time horizons, highlighting its pivotal role in driving environmental sustainability. Trade openness was found to be positively related to emissions in the long run, indicating that greater integration into global markets may have been accompanied by environmentally detrimental outcomes, potentially through increased industrial activity or the transfer of polluting industries. Lastly, the error correction term was both negative and significant, with a coefficient of –0.868073, suggesting that deviations from the long-run equilibrium are corrected at a speed of roughly 87% annually.

The results of this study offer several meaningful guidance for shaping India's pursuit of sustainable development. First, the identified U-shaped link between GDP and emissions suggests that economic growth in India, beyond a certain point, intensifies environmental degradation, thereby rejecting the EKC hypothesis. Policymakers should therefore prioritize a transition to low-carbon development by promoting green technologies, enforcing stringent environmental regulations, and integrating sustainability into growth planning. Second, the negative association between renewable energy use and emissions underscores the need to accelerate investment in clean energy and strengthen policy support for renewable sources. Third, as trade openness is found to contribute to higher emissions over time, trade policy should be aligned with environmental goals by encouraging cleaner production standards and promoting green exports. Lastly, although FDI did not significantly influence emissions, India has the opportunity to attract green FDI by offering targeted incentives and embedding environmental safeguards into investment regulations. These measures collectively can support India's path toward sustainable, inclusive, and environmentally responsible economic growth.

Declaration of Competing Interest

The authors declare that there is no known competing financial interests or personal relationships that could influence the research conducted in this paper.

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