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Greening the Nation: India's Path Towards Sustainable Future

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This study aims to examine the non-linear impacts of green finance and renewable energy consumption on carbon emissions in India. To our knowledge, no previous research has investigated this relationship in the Indian context. The study employs the Markov regime-switching model from 2000Q1 to 2022Q4. The results reveal that green finance lowers emissions in Regime 1 but raises them in Regime 2. In contrast, renewable energy consumption does not affect emissions in Regime 1 but helps reduce emissions in Regime 2. The findings underscore the importance of continued support for green finance initiatives and the expansion of renewable energy infrastructure.

I. Introduction

Current research increasingly focuses on reducing emissions to promote a sustainable environment. The increase in emissions has contributed to higher global temperatures and changes in climate patterns globally. Addressing this issue requires more efforts to improve environmental conditions and support sustainable economic development by controlling rising emissions levels.

Recent research by Bakry et al. (2023), Behera et al. (2024), and Sadiq et al. (2024) has investigated the impact of green finance and renewable energy usage on CO₂ emissions. Through methodologies such as CS-ARDL and VECM, these studies demonstrate that green finance and renewable energy effectively reduce emissions in BRICS and developing nations. However, they do not consider potential non-linear dynamics or regime shifts.

This paper contributes to the existing literature by employing a Markov switching approach to analyze the relationships between green finance, renewable energy, and CO₂ emissions in India. Additionally, it incorporates technological innovations, trade in low-carbon technology, and foreign direct investment to address omitted-variable bias.

The selection of these variables is grounded in previous research and theoretical frameworks. Green financial instruments contribute to reducing carbon emissions by funding environmentally sustainable projects (Wang et al., 2022). Renewable energy is crucial for addressing the issue of increasing carbon emissions (Zhang et al., 2022). Technological innovation advances the development of more efficient technologies that can mitigate emissions, although this topic remains subject to debate (Zhang et al., 2022).

Foreign Direct Investment (FDI) often leads to higher carbon emissions by attracting energy-intensive industries reliant on fossil fuels, but it can also facilitate the transfer of green technologies from developed to developing countries (Deng et al., 2024). The trade of low-carbon technologies effectively reduces emissions and improves environmental quality (Wei et al., 2023).

Green finance derives its theoretical foundations from the Equator Principles (EP, 2003) and the Principles for Responsible Investment (PRI, 2006). Literature in energy economics links emissions and energy consumption through the theory of energy-induced emissions (EIE) (Zaman & Abd-el Moemen, 2017). Population (P), Affluence (A), and Technology (T) are determinants of environmental impacts (I). Our model incorporates technological innovation based on the IPAT hypothesis, which is rooted in the technology acceptance paradigm (Li et al., 2024). According to the pollution havens and halo hypothesis, FDI both increases and decreases emissions (Deng et al., 2024). The Pollution Halo hypothesis also elucidates the trade-environment relationship by promoting the diffusion of green technology through eco-friendly commerce (Wei et al., 2023).

For our analysis, we utilized annual data spanning from 2000 to 2022. To enhance the robustness of our study and capture greater variability in the variables, we converted this annual data into quarterly observations through interpolation. Consequently, the data presented throughout the study is on a quarterly basis. Our empirical findings indicate that green finance investments reduce emissions in Regime 1 while they increase emissions in Regime 2. Furthermore, the use of renewable energy decreases emissions in Regime 2 but has no impact in Regime 1.

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Table 1. Data description

Variable	Description	Source	Literature	Mean	SD	Min	Max
CO	CO ₂ emissions per capita (metric tons)	WDI	Zhang et al., 2022	-1.141	0.243	-1.512	-0.795
GF	International financial received for clean energy (millions of constant 2020 US\$)	IRENA	Wang et al., 2022	18.492	1.288	15.039	20.243
RE	Renewable energy consumption (% of total final energy consumption)	WDI	Zhang et al., 2022	2.262	0.129	2.096	2.470
FDI	Foreign direct investment, net inflows (% of GDP)	WDI	Deng et al., 2024	-0.978	0.441	-1.974	-0.041
LCT	Trade in low-carbon technology (US\$)	IMF	Wei et al., 2023	-1.767	0.345	-2.543	-1.298
RD	Research and development expenditure (% of GDP)	WDI	Zhang et al., 2022	-1.707	0.092	-1.868	-1.530

This table describes the variables and reports their summary statistics.

In light of these results, the study explores how the adoption of green finance and renewable energy consumption, along with foreign direct investment (FDI) inflows, technological innovation, and low-carbon technology trade, can assist in outlining India's priorities for climate action. However, the non-linear relationship between finance and ecology remains relatively unexplored in the Indian context and warrants further investigation.

II. Data and Methodology

A. Data

Table 1 presents a comprehensive overview of the variables analyzed in the study, including their descriptions, data sources, references to pertinent literature, and summary statistics.

All variables are converted to their natural logarithm. Significant differences exist between the minimum and maximum values of carbon emissions per capita (CO), international finance received for clean energy or green finance (GF), renewable energy consumption (RE), foreign direct investment (FDI), trade in low-carbon technology (LCT), and research and development expenditure (RD). The averages and standard deviations show considerable variability within each time series data. We applied the Brock, Dechert, and Scheinkman (BDS) test (1987) to examine potential non-linearity in the finance-ecology relationship. This test checks if increments in a data series are independent and identically distributed. Rejecting the null hypothesis indicates non-linearity. Table 2 shows significant BDS test results across all dimensions (D) at a 1% significance level, suggesting that MS is suitable for studying finance-ecology relationships.

B. Methodology

According to the empirical literature, our model can be written in functional form as

$$CO_t = f(GF_t, RE_t, RD_t, LCT_t, FDI_t) \quad (1)$$

Where CO denotes carbon emissions per capita (measured in metric terms), GF represents green finance (in US dollars), RE signifies renewable energy consumption (as a % of total final energy consumption), RD refers to research and development expenditure (as a % of GDP), LCT indicates trade in low-carbon technology (in US dollars), and FDI denotes foreign direct investment (net inflows, as a % of GDP).

The function described above can be transformed into an econometric model by incorporating a constant (C_0) and an error term (ε_t):

$$CO_t = C_0 + \alpha_1 GF_t + \alpha_2 RE_t + \alpha_3 RD_t + \alpha_4 LCT_t + \alpha_5 FDI_t + \varepsilon_t \quad (2)$$

B.I. Regime switching approach

The current study employs the Markov Switching Dynamic Regression (MSDR) method of Hamilton (1989) to investigate the non-linear impact of GF and RE on carbon emissions, along with other control variables, such as RD, LCT, and FDI. The Markov Switching (MS) model has been chosen due to the growing emphasis on green finance policy since 2007. We applied the 2-state Markov Switching (MS (2)) model to examine this relationship. Mean (μ_{st}), variance (σ_{st}), GF_{st} , and RE_{st} are treated as regime-switching variables (coefficients that change with the regime s), while RD, FDI, and LCT are non-switching variables (coefficients that do not change with the regime). Time series evolves around two unobservable states (S_t , where $t = 1, 2$). MS (2) can be specified as follows:

$$CO_t = \mu_{st} + \beta_{st} Z_t + \sum_{i=1}^3 \theta_i X_i + \varepsilon_{st} \quad (3)$$

where μ_{st} represents the state-dependent intercept, Z_t denotes the state-dependent variable, X_i represents the state-invariant variables, and ε_{st} indicates that errors may vary across different states or regimes. The probabilities will be

$$S_t = \begin{cases} 1 & \text{with probability } p_{11} \\ 2 & \text{with probability } p_{22} \end{cases} \quad (4)$$

With the transition probability matrix,

Table 2. BDS test

BDS Statistic	D2	D3	D4	D5	D6
CO	0.207***	0.352***	0.451***	0.517***	0.558***
GF	0.130***	0.201***	0.246***	0.277***	0.287***
RE	0.204***	0.345***	0.442***	0.508***	0.550***
RD	0.183***	0.301***	0.377***	0.425***	0.455***
LCT	0.205***	0.350***	0.451***	0.521***	0.568***
FDI	0.170***	0.280***	0.347***	0.385***	0.402***
Residual	0.140***	0.218***	0.255***	0.269***	0.269***

The table displays the findings of the BDS test, conducted with 100,000 bootstrap replications. The outcome suggests rejecting the null hypothesis, indicating non-linear dependence within the series.

Table 3. Stationarity test results

ADF Test				
	Constant		Constant & Trend	
	I(0)	I(1)	I(0)	(1)
CO	-2.360	-3.343***	-2.301	-4.009***
GF	-2.435	-4.437***	-2.421	-4.488***
RE	-2.749*	-2.896**	-2.690	-3.752***
RD	-1.945	-5.397***	-3.387**	-5.599***
FDI	-4.164***	-7.340***	-4.586***	-7.377***
LCT	-2.890**	-6.409***	-2.906	-6.895***

Zivot-Andrew test				
CO	-0.856 (2019Q2)	-4.587* (2019Q1)	-3.500 (2017Q3)	-3.574 (2013Q2)
GF	-3.460 (2010Q2)	-6.196*** (2010Q2)	-3.907 (2019Q2)	-6.308*** (2010Q2)
RE	-2.574 (2019Q2)	-4.540 (2019Q2)	-2.768 (2016Q2)	-3.592 (2019Q2)
RD	-3.869 (2004Q1)	-6.888*** (2008Q2)	-4.028 (2006Q2)	-7.251*** (2005Q2)
FDI	-5.332** (2005Q2)	-7.803*** (2005Q2)	-5.785*** (2005Q2)	-8.005*** (2008Q2)
LCT	-3.187 (2004Q2)	-7.910*** (2009Q1)	-6.476*** (2007Q2)	-8.099*** (2008Q2)

This table shows ADF and ZA test results. I(0) and I(1) indicate that the indicators are stationary at the level or the first difference. (.) indicates the ZA test break date. Note: *, **, and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

$$P_r = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} \text{ where } p_{11} + p_{12} = p_{21} + p_{22} = 1 \quad (5)$$

where the odds of staying in regimes 1 and 2 are denoted by p_{11} and p_{22} , respectively, while the odds of switching regimes are denoted by p_{12} and p_{21} . Thus,

$$P_{ij} = P_r(S_t = i | S_{t-1} = j) \text{ for all } i, j = 1 \text{ and } 2 \quad (6)$$

III. Empirical Findings

A. Stationarity Test

Table 3 presents the outcomes of the Augmented Dickey-Fuller (1979) test and the Zivot-Andrews (2002) structural break test for detecting structural changes. The findings indicate that the variables under examination are stationary either at levels or at the first difference.

B. Markov-switching model

Table 4 presents the findings of the MS (2) model, where the two states represent distinct emission regimes. Regime 1 is characterized by higher average carbon emissions ($\mu_1 > \mu_2$), indicating a high-emission regime, while Regime 2 is associated with lower emissions, representing a low-emission regime. Volatility (σ) is very low in both states.

It is observed that the relationship between DGF and DCO varies across regimes. In Regime 1, a 1% increase in DGF resulted in a reduction of DCO by 0.0068%, whereas in Regime 2, DCO increased by 0.0066% in response to the same increase in DGF . However, the effect of DRE on DCO is insignificant in Regime 1 but is negative and significant in Regime 2. Specifically, a 1% increase in DRE reduced DCO by 1.5136% in Regime 2.

Table 4. MS Model

Variable	MS(2)
Regime 1	
μ_1	0.0507*** (0.0185)
σ_1	0.0036*** (0.4182)
DGF_1	-0.0068** (0.0032)
DRE_1	0.2161 (0.3196)
Regime 2	
μ_2	0.0330* (0.100)
σ_2	0.0047*** (0.1058)
DGF_2	0.0066*** (0.0014)
DRE_2	-1.5136*** (0.1016)
Common	
RD	0.0207* (0.0109)
FDI	-0.0037*** (0.0014)
$DLCT$	-0.0715*** (0.0147)
Probability matrix	$\begin{pmatrix} 0.1548 & 0.8451 \\ 0.1548 & 0.8451 \end{pmatrix}$
Expected Duration	Regime1 1.1832 years Regime2 6.4573 years

This table shows MS (2) model estimates (2000Q1-2022Q4). The variables GF, RE, and LCT are in their first difference. (.) represents SE. Subscripts 1 and 2 reflect regimes 1 and 2, respectively. Note: *, **, and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Regarding the non-switching variables, the findings indicate that RD has a significant positive impact on DCO . Specifically, a 1% increase in RD corresponds to an increase in DCO by 0.0207%. This relationship suggests that research activities consume significant electricity, thereby increasing fossil fuel use and carbon emissions (Petrović & Lobanov, 2020). On the other hand, FDI shows a significant negative correlation with DCO , indicating that a 1% rise in FDI leads to a decrease in DCO by 0.0037%. This could be due to developed countries transferring greener technology to developing nations through FDI , thereby reducing emissions (Deng et al., 2024). Similarly, a 1% increase in $DLCT$ decreases DCO by 0.0715% (Wei et al., 2023).

The transition probabilities further elucidate that Regime 2 (low-emission) is more persistent than Regime 1, with a higher likelihood of remaining in the low-emission state over time ($p_{22} > p_{11}$). Additionally, there is a greater chance of transitioning from Regime 1 to Regime 2, suggesting a potential for policy interventions to facilitate the

shift towards lower emissions ($p_{12} > p_{21}$) (refer to [Figure A](#) in the Appendix).

One possible explanation for these transition probabilities lies in the evolving policy landscape related to climate change and sustainability. For example, in 2008, the formulation of the National Action Plan on Climate Change signaled a significant commitment by the Indian government to address climate change and mitigation efforts. Initiatives such as the establishment of a climate change finance unit within the Ministry of Finance in 2011, the introduction of the Bombay Stock Exchange's energy-efficient green index in 2012, and revisions to the RBI's Priority Sector Lending guidelines to include renewable energy projects reflect a concerted effort to promote green finance and renewable energy adoption. These policy changes contributed to a gradual transition from high-emission practices to lower-emission alternatives.

The analysis also shows that Regime 1 (1.1832 years) is shorter than Regime 2 (6.4573 years). This shows that Regime 2, with lower emissions, lasts longer than Regime 1, which has higher emissions.

IV. Conclusion

The study employs the MS model to investigate the non-linear relationship between the variables. The model reveals that GF reduces emissions in Regime 1 and increases them in Regime 2. RE , on the other hand, does not affect emissions in Regime 1 but reduces them in Regime 2. FDI and LCT reduce emissions among the non-switching variables, whereas RD increases them.

These findings underscore the importance of adaptive and targeted interventions to effectively address emissions reduction goals in changing economic and policy landscapes. India needs a permanent green finance policy to integrate sustainability into decision-making to meet its climate goals. Prioritizing nuclear, solar, and wind energy and policies promoting green technologies will reduce emissions. Moreover, strengthening environmental regulations and standards to enforce sustainable and eco-friendly practices among foreign investors is imperative. These measures will help India reach net zero by 2070.

Future research will focus on cross-country analyses, particularly in countries with established green financial systems, to compare advantages and experiences across nations.

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Appendix

Simple Switching Filtered/Smoothed Regime Probabilities

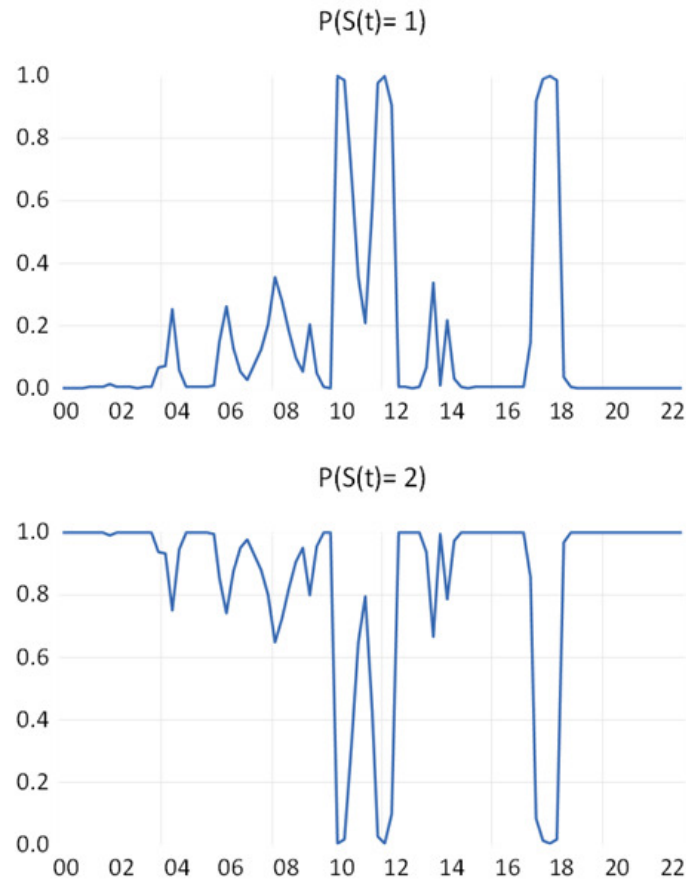


Figure A. Switching Regimes Probability Graph

The chart displays the likelihood that the system is in each of the two states (regimes) at any given time. In this case, the two regimes are: low-emission and high-emission states. The smoothed probability graph above indicates a higher probability of being in State 2 (low emission state) than State 1 (high emission state).