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Macroeconomic Environmental Interactions and the Path of India's Energy Transition

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Abstract

India's economic growth has long been intertwined with environmental challenges, particularly as it seeks to align development goals with climate commitments under the Paris Agreement. Despite increasing investments in green finance and renewable energy, structural barriers persist, limiting the pace of energy transition. This paper provides new empirical insights into the dynamic interactions between macroeconomic, environmental, and energy variables in India using a Bayesian Vector Autoregression (BVAR) framework over the period 2000–2020. Major findings include stagnant renewable energy consumption (REC) through 2027 amid rising CO_2 emissions and declining R&D spending, a negative impact of PM2.5 pollution and CO_2 emissions on REC, and strong path dependency in REC trends. Impulse response functions reveal that foreign direct investment (FDI) initially suppresses but later promotes REC, while paradoxical effects between R&D spending and environmental trade highlight misaligned policy incentives. To support India's Viksit Bharat 2047 vision, the study recommends targeted reforms, including redirecting FDI toward renewable projects, boosting innovation funding for energy technologies, and realigning environmental trade policies to enhance energy transition outcomes.

***JEL Classification** : E31, Q54, C32, O13*

I. INTRODUCTION

India's economic development path is progressively shaped by the twin imperatives of industrialization and environmental sustainability. Being one of the world's largest greenhouse gas emitters, India plays a pivotal role in global climate action through its commitments under the Paris Agreement (UNFCCC, 2015). The country vowed to reduce emissions intensity by 45% from 2005 levels by 2030 and to achieve net-zero emissions by 2070 (Government of India, 2021; IMF, 2024). These areas are dominant to India's Viksit Bharat 2047 vision, which visualizes a future where economic growth is distinguished from environmental degradation. Even with increasing investments in green finance and renewable energy there exists a structural barrier limiting the renewable energy adoption (Cui et al., 2023; Liu et al., 2023). Green finances emerged as a key mechanism for promoting clean energy adoption and reducing carbon footprints (Zhang et al., 2022). However empirical evidence estimating how financial flows, macroeconomic indicators, and environmental pressures interact to shape India's energy transition remains partial (IMF, 2024). Most studies focus on aggregate impacts without accounting for feedback loops or forecasting future trends under current conditions (Jafar, 2000).

The turning point in global climate governance, came with the signing of the Paris Agreement in COP21 in 2015, which highlighted the need for countries to shift towards low carbon economies and enhance climate resilience through sustainable financial systems (Yang & Park, 2020). India sanctioned the agreement in 2016, confirming its commitment to sustainable development by aligning it with Mahatma Gandhi's birth anniversary, representing the moral imperative of ecological stewardship (Government of India, 2021). At the domestic level, the period from 2000 to 2020 was marked by significant transformation in India's environmental and economic policies. While the economy grew rapidly, challenges such as rising CO_2 emissions, air pollution, and energy insecurity persisted (Chakraborty & Mukherjee, 2010; Singh & Jha, 2019). Important commitments include increasing the share of non-fossil fuel-based electricity generation capacity to 50% by 2030 and enhancing forest cover to create additional carbon sinks (Roemer & Haggerty, 2021).

Understanding the dynamic interlinkages between energy use, economic indicators, and environmental impacts is crucial for formulating effective policies that support long-term sustainability (IMF, 2024). To address this gap, our approach builds on earlier studies using multivariate time series models to explore energy, environment & economy linkages (Sims, 1980; Koop et al., 1996; Kilian & Lutkepohl, 2017). We apply a Bayesian Vector Autoregression (BVAR) model to assess the impact of eight key indicators - renewable energy consumption (REC), CO_2 emissions, PM2.5 levels, foreign direct investment (FDI), R&D expenditure, labour force participation, inflation, and environmental trade on REC over the period 2000 to 2020. We extend the analysis by forecasting trends up to 2027, offering novel insights into policy dynamics to enhance REC in alignment with India's Viksit Bharat 2047 vision and Paris Agreement renewable energy goals. Renewable energy consumption (REC), defined as the share of renewable energy in total final energy consumption, is selected as the focal variable due to its direct relevance to

India's commitment to achieve 50% non-fossil fuel-based electricity capacity by 2030 and net-zero emissions by 2070 (Government of India, 2021).

II. LITERATURE REVIEW

While the dynamic interlinkages between energy use, economic indicators, and environmental impacts have been widely studied for India and similar economies, this section reviews key prior research thematically to highlight gaps addressed by the current study.

Environmental Determinants of Renewable Energy Adoption

Aguirre and Ibikunle (2014) employ panel data regression analysis on a global sample to identify the primary economic, institutional and policy factors influencing renewable energy growth. Their use of fixed effects panel regressions allows them to control for unobserved heterogeneity and robustly identify determinants operating across countries. Hoang et al. (2024) employ time-series and causality modelling to dissect the dynamic relationships linking economic growth, energy use and CO_2 emissions, revealing bidirectional causalities and underscoring the necessity for integrating renewables to achieve conjoined economic-environmental objectives. Dogan and Seker (2018) analyse the drivers of renewable energy development across European Union countries using panel cointegration techniques. Their empirical strategy includes panel unit root tests, cointegration tests and fully modified ordinary least squares (FMOLS) estimation, thus capturing both the presence of long-term relationships and the magnitude of individual factors across the EU. Ozturk and Saboori (2021) utilize an autoregressive distributed lag (ARDL) bounds testing approach to examine the short- and long-run impacts of policy, economic and social variables on renewable energy consumption in the United States. This method enables an explicit assessment of both immediate and persistent effects of key determinants.

Economic Enablers of Energy Transition

Ewah et al. (2021) investigate how digitalisation acts as a catalyst for sustainable energy transitions in African economies, particularly Nigeria and South Africa, illustrating the impact of smart infrastructure and digital platforms on sectoral transformation.

Innovation and Trade in Sustainable Energy Systems

Shahbaz et al. (2024) utilize panel econometric modelling to examine the relationship between renewable energy finance, economic development and environmental outcomes in the OECD and BRICS countries, underscoring the pivotal role of financial flows and governance quality in shaping transition pathways. In the Belt and Road Initiative context, Liu et al. (2023) employ the CS-ARDL framework to reveal the asymmetric effects of financial openness, trade integration and capital formation on energy sustainability, exposing complex cross-border interdependencies. Zhao et al. (2024) demonstrate, through transmission mechanism modeling, that digital innovation directly strengthens both the financial resilience and green transition capability of energy companies, substantiating the value of digital investments for sustainability performance. Likewise, Qureshi et al. (2024) explore how financial inclusion, digital strategies and governance converge to enhance environmental performance across OECD nations, arguing for the mainstreaming of digital innovation within policy frameworks. Meanwhile, Lin et al. (2024) uniquely approach "multidimensional green growth" using scenario analysis and panel data to link targeted green finance and innovation policy to sustainability performance across economic cycles.

Theoretical Frameworks of Sustainability Transitions

Sustainability transition scholarship has expanded rapidly over recent years, offering insights relevant to the green growth and renewable energy transitions of emerging economies. For instance, Markard (2024) presents a comprehensive analysis of sustainability transitions in the twenty-first century, highlighting the intertwined roles of innovation, systemic transformation and policy design across global contexts. Complementing this focus, Mahmood et al. (2022) deploy science mapping and co-word analysis to delineate evolving thematic concentrations in renewable energy research, revealing a pronounced shift toward

interdisciplinary integration and alignment with the Sustainable Development Goals. Loorbach et al. (2017) build on this by conceptualizing sustainability transitions as processes deeply rooted in socio-technical, institutional and ecological change, emphasizing the crucial interplay between deliberate governance and spontaneous market dynamics.

Collectively, these studies underscore that successful energy and sustainability transitions are multidimensional phenomena, shaped by contextual drivers ranging from technological capability and digitalisation to financial architecture and policy commitment. Together, they provide a holistic scholarly backdrop that both situates and justifies further research employing dynamic, country-specific modelling as in the present Indian case. However, they lack dynamic scenario modelling and the ability to capture feedback effects among variables. Unlike the static panel regressions of Aguirre and Ibikunle (2014) or the ARDL approach of Ozturk and Saboori (2021), which fail to account for interdependent dynamics, this study employs a Bayesian Vector Autoregression (BVAR) model tailored to the Indian context to overcome these shortcomings. Additionally, while Dogan and Seker (2018) rely on cointegration techniques to explore long-term relationships across the European Union without forward-looking analysis, this study extends the analysis with forecasts up to 2027, addressing this gap with a perspective tailored to India's unique policy landscape, including its Viksit Bharat 2047 vision and Paris Agreement commitments. Furthermore, the inclusion of policy-relevant variables such as environmental trade and an emphasis on lagged effects, which are absent in the broader regional or global analyses of these prior works, enhance the complex understanding of India's energy transition provided by the BVAR approach.

III. METHODOLOGY

The selection of the Bayesian Vector Autoregression (BVAR) model is strategically justified by its ability to address the methodological challenges posed by this study's dataset and research objectives. With only 21 annual observations (2000–2020), classical VAR models risk overfitting due to their reliance on unrestricted parameter estimation, whereas BVAR's incorporation of informative priors, such as the Minnesota prior, stabilizes estimates by leveraging theoretical expectations about lag structures and variable relationships. Compared to the Autoregressive Distributed Lag (ARDL) approach, which is effective for cointegration but less suited for capturing multivariate feedback loops, BVAR excels in tracing impulse responses across REC, environmental and economic variables. Panel methods, while robust for cross-country analysis, fail to account for India-specific dynamics, such as policy shocks from the Paris Agreement or regional coal dependency. BVAR's suitability is further validated by its capacity to handle nonlinear lagged effects and small-sample uncertainty, making it ideal for modeling India's energy transition. This approach enables robust forecasting up to 2027, aligning with the Viksit Bharat 2047 vision and supports the study's goal of integrating advanced econometrics with policy-relevant insights. This methodological advantage underpins the detailed implementation of BVAR, which leverages prior information to enhance estimation accuracy in India's constrained data environment.

The BVAR framework allows us to incorporate prior information and manage uncertainty more effectively than classical VAR models, especially in small samples (Koop, 2009), to assess the impact of key indicators on renewable energy consumption (REC). This methodological consistency ensures robustness in capturing the nonlinear dynamics and lagged effects inherent in India's energy transition process. Recent literature highlights the importance of institutional quality and policy design in determining the success of renewable energy initiatives (Yang & Park, 2020). In contrast, developing economies like India face unique challenges due to inadequate infrastructure, fragmented regulatory frameworks and insufficient public-private coordination (Roemer & Haggerty, 2021). India's coal-dependent regions also highlight the socio-economic complexities involved in transitioning to cleaner energy sources (Roemer & Haggerty, 2021). Moreover, the efficiency of green financing mechanisms depends heavily on local governance structures and market motivations (Liu et al., 2023). Structural exposures such as lack of alternative employment opportunities, weak social safety nets and job dependency on fossil fuels underscore the need for a just transition that balances environmental goals with economic equity (Della Bosca & Gillespie, 2018b). This paper contributes to the growing body of research on energy transitions in emerging economies by presenting new empirical evidence on India's energy dynamics, focusing on REC and forecasting future trends under current conditions. By integrating advanced econometric techniques with policy insights, our study provides timely guidance for aligning India's Viksit Bharat 2047 vision with its international climate obligations.

In order to increase estimation accuracy, particularly in small samples, the Bayesian Vector Autoregressive (BVAR) model incorporates prior beliefs into the traditional Vector Autoregressive (VAR) methodology. The BVAR incorporates informative priors that represent theoretical expectations regarding the structure of the economy, in contrast to conventional VAR models that treat all variable relationships equally. One widely used specification is the Minnesota Prior, which assumes that own lags have stronger influence than cross-variable lags, coefficients decline with lag length and variables follow random walk behaviour unless otherwise specified.

Figure.No.1 Architectural Framework of the BVAR Model

The general form of a VAR(p) model:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots \cdots + A_p Y_{t-p} + \epsilon_t$$

1

Where Y_t is an $n \times 1$ vector of endogenous variables, A_i are coefficient matrices and ϵ_t is a vector of normally distributed error terms with mean zero and covariance matrix Σ. This formulation assumes that each variable depends on its own lags and those of other variables in the system. In the Bayesian framework, we update our beliefs about these parameters using Bayes' theorem:

$$P\left(\frac{A}{Y}\right) \alpha\, P\left(\frac{Y}{A}\right) . P(A)$$

2

Here, $P\left(\frac{Y}{A}\right)$ represents the likelihood function derived from the data, while $P(A)$ reflects the prior distribution based on existing knowledge or theoretical assumptions. The posterior distribution $P\left(\frac{A}{Y}\right)$ combine both sources of information to yield more robust parameter estimates. Under the assumption of a multivariate normal prior, the prior distribution is expressed as:

$$vec(A) \sim N(\mu, V) \qquad (3)$$

Where $vec(A)$ stacks the columns of the coefficient matrices into a single vector. Using Markov Chain Monte Carlo (MCMC) methods, specifically the Gibbs sampler, we iteratively sample from the full conditional posteriors of each parameter set. This allows us to approximate the posterior distribution even when analytical solutions are not feasible. After estimation, we compute impulse response functions (IRFs) to trace how a one standard deviation shock in one variable affects others over time:

$$IRF(h) = \phi_h . e_j$$

4

Where ϕ_h is the moving average representation of the VAR at horizon (h), and e_j selects the j-th shock. Finally, forecast error variance decomposition (FEVD) quantifies the proportion of forecast error variance explained by each variable, helping to assess their relative importance in shaping India's energy transition dynamics.

IV. DATA

This study employs a quantitative approach covering key economic and environmental indicators relevant to sustainable growth for India over the period 2000–2020. Data on renewable energy consumption, CO2 emissions, PM2.5 emissions, environmental trade, R&D expenditure, FDI, and workforce participation were collected from reliable sources such as the World

Bank, International Energy Agency (IEA), and Reserve Bank of India. All variables are converted into a uniform format to facilitate econometric modelling. The Dependent Variable is the Renewable Energy Consumption represents Renewable energy consumption is the share of renewable energy in total final energy consumption. The Independent variables includes Environmental Factors: CO2 emissions PM2.5 emissions, environmental trade (ET) and Research and development expenditure (RD) and Economic Factors: foreign direct investment (FDI), and labour force participation (LR), GDP Deflator proxy for Inflation.

This study aims to estimate the impact of environmental and economic factors on Renewable Energy Consumption (REC) in India using a time series regression model over the period 2000 to 2020. The dependent variable is the share of renewable energy in total final energy consumption, while the independent variables include both environmental indicators and economic indicators.

Table.No.1 Description of Variables Used in the BVAR Analysis

VARIABLE	SYMBOL	DESCRIPTION	MEASUREMENT / TRANSFORMATION
Renewable Energy Consumption (% of total energy consumption)	REC	Renewable energy consumption refers to the share of energy derived from solar, wind, hydro, geothermal, and bioenergy as a percentage of total final energy consumption within an economy. It measures the extent to which a country utilizes clean and sustainable energy sources in its overall energy mix.	Share of renewables in total final energy consumption; logged (LOGREC) to address skewness and ensure stationarity.
CO2 emissions (metric tons per capita)	CO2	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement.	Per capita metric tons; levels (no log) but differenced in BVAR lags to address non-stationarity.
PM2.5 emissions (micrograms per cubic meter)	PM2_5	PM2.5 emissions is the average level of exposure of a nation's population to concentrations of suspended particles measuring less than 2.5 microns in aerodynamic diameter. Exposure is calculated by weighting mean annual concentrations of PM2.5 by population in both urban and rural areas.	Micrograms per cubic meter; levels, adjusted for population-weighted exposure.
Environmental trade (% of GDP)	ET	Total trade in environmental goods as a percent of GDP refers to the sum of a country's exports and imports of environmental goods, expressed as a percentage of its Gross Domestic Product (GDP). This indicator reflects the extent to which an economy is engaged in the global market for products that help reduce environmental damage and support sustainable development.	Percentage of GDP; levels, representing total trade value.
R&D expenditure (% of GDP)	RD	R&D covers basic research, applied research, and experimental development expenditures.	Percentage of GDP; levels, aggregated from public and private spending.
Foreign Direct Investment (% of GDP)	FDI	FDI shows net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors, and is divided by GDP.	Percentage of GDP; logged (LOGFDI) to stabilize variance and address skewness.
Workforce Participation (% of total population above 15+)	LR	Labor force participation rate is the proportion of the population ages 15 and older that is economically active	Percentage of population aged 15+; levels, reflecting economic activity rate.
GDP Deflator	INF	Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole.	Annual percentage growth rate; levels, proxying inflation dynamics.

V. EMPIRICAL ANALYSIS

This study builds on Bayesian time-series foundations and sustainability transition frameworks widely used in macro-environmental analysis (Litterman, 1986; Pesaran & Shin, 1998; IMF, 2024; Lin et al., 2024; Qureshi et al., 2024). The empirical analysis presented in this study utilizes a Bayesian Vector Autoregression (BVAR) framework to examine the dynamic interactions between key macroeconomic and environmental variables in India over the period 2000 to 2020, and to forecast up to 2027. The results provide valuable insights into India's energy transition dynamics, particularly in relation to renewable energy consumption (REC), CO_2 emissions, PM2.5 pollution, foreign direct investment (FDI), R&D expenditure, and other relevant indicators.

The macroeconomic and environmental factors in India exhibit dynamic interactions, as demonstrated by the Impulse Response Functions (IRFs) derived from the Bayesian Vector Autoregression (BVAR) model. The reaction of Renewable Energy Consumption (REC) and additional indicators over time is shown by a one standard deviation shock to each variable. The significance of steady policy backing is underscored by REC's robust resilience and favourable reaction to its own disturbances. However, shocks to PM2.5 pollution and CO_2 emissions negatively affect REC, suggesting that heightened environmental stress does not immediately accelerate the shift to clean energy. The early reduction of REC due to foreign direct investment (FDI) is succeeded by a minor positive shift, indicating that the advantages of green capital inflows require time to emerge. Surprising short-term impacts are evident in R&D expenditure and environmental trade, indicating potential misalignments or delays in realizing investment outcomes

This section is split into two primary components: (1) the BVAR estimates based on historical data, showing notable lagged effects and variable interdependencies; and (2) the projected values for 2021–2027, forecasting future trends based on existing policy frameworks

Table 2
BVAR Coefficient Estimates for India (2000–2020)

Regressor	GDP_ DEFLATOR	LOGFDI	LOGREC	CO2	ET	LR	PM2_5	RD
GDP_ DEFLATOR(-1)	0.085058	1.81E-05	-0.000594	0.001858	0.010156	0.010702	-1.61E-05	0.00149
GDP_ DEFLATOR(-2)	0.022508	1.55E-05	-0.000133	0.000418	0.00251	0.003912	2.71E-07	0.000331
LOGFDI(-1)	-15.31363	0.358618	-0.24297	-1.486489	-4.735245	-19.67172	-0.968724	-0.859735
LOGFDI(-2)	-9.770569	0.071518	0.050338	-0.569787	-2.105213	-11.6395	-0.246376	-0.505315
LOGREC(-1)	-9.514179	0.000469	0.427971	-1.701517	-2.092336	1.252333	-0.208305	0.011322
LOGREC(-2)	-0.251891	0.003733	0.075529	-0.356677	-0.263033	0.88939	-0.057115	0.05748
CO2(-1)	-0.688214	-0.001905	-0.024648	0.129369	0.11117	0.086491	0.026759	-0.013167
CO2(-2)	-0.236378	-0.000815	-0.003433	0.01886	-0.005352	-0.006174	0.007162	-0.008515
ET(-1)	0.607815	0.000387	-0.009471	0.032244	0.104187	0.223271	0.003323	0.017477
ET(-2)	0.220088	0.00026	-0.002857	0.008485	0.017116	0.043081	0.000793	0.002675
LR(-1)	0.084168	0.000201	-0.001351	0.002225	0.011069	0.065252	0.000472	0.003421
LR(-2)	0.070649	6.81E-05	-0.00043	0.000604	0.002261	0.00699	6.55E-05	0.000554
PM2_5(-1)	-11.56259	-0.053453	-0.121277	0.933227	-0.663294	-0.231707	0.429751	-0.469696
PM2_5(-2)	-4.997032	-0.016474	-0.014728	0.200255	-0.278384	-0.681827	0.106423	-0.144416
RD(-1)	7.330919	0.00524	-0.031314	0.013205	0.577127	2.073285	-0.01009	0.151261
RD(-2)	1.906498	0.00233	-0.012306	0.01942	0.122568	0.344855	-0.001726	0.023599
C	118.017	1.231664	1.70522	3.71236	19.46283	53.52844	4.208891	5.112859
Source: Secondary Data-author computed								

The BVAR model estimations provide important insights into the short-term interactions among the chosen variables: Renewable Energy Consumption (REC), CO_2 emissions, PM2.5 emissions, Environmental Trade (ET), R&D expenditure (RD), Foreign Direct Investment (FDI), Labour Force Participation (LR), and the GDP Deflator (which serves as an inflation proxy). Lagged values of REC show statistical significance, especially at the first lag (coefficient = 0.427971), reflecting a robust persistence in the adoption of renewable energy. This implies that previous renewable energy usage substantially affects present patterns, highlighting the necessity of consistent policy and long-term strategies in the energy industry.

FDI shows a mixed impact on REC, FDI has a negative coefficient (-15.31363), suggesting that initial inflows may not be directed toward green sectors or may displace domestic investments, at the first lag. However, at the second lag (-9.770569), the effect becomes less negative, indicating a possible realignment of foreign capital towards sustainable projects over time. This changing behavior emphasizes the necessity for specific FDI policies to guarantee conformity with national environmental objectives. Both CO_2 and PM2.5 emissions show detrimental impacts on REC in the short term. As an illustration, the CO_2 coefficient at the initial lag is -0.024648, whereas PM2.5 at that same lag is -0.121277. These results imply that increasing pollution levels do not automatically lead to a transition to cleaner energy, a surprising outcome that may stem from poor enforcement of environmental laws or insufficient public awareness. Inflation (GDP Deflator) and Labour Force Participation (LR) exhibit minimal impact on REC. The inflation coefficients are minor and vary across lags, suggesting that

macroeconomic stability, although significant, does not directly influence renewable energy usage. Likewise, LR's favourable yet negligible connection with REC suggests that job levels by themselves may not encourage green investment in the absence of supportive policies

Environmental Trade (ET) shows a positive but delayed effect on REC, with the strongest influence at the second lag (0.220088). This suggests that trade in environmental goods contributes to green development, albeit with a time lag. Conversely, R&D expenditure initially shows a negative relationship with REC, likely due to delays in translating research into commercial applications. However, this effect diminishes over time, pointing to the eventual benefits of innovation in clean energy technologies. The model demonstrates a good fit, particularly for REC, as evidenced by high R-squared values. However, the lower adjusted R-squared indicates some risk of overfitting, especially given the relatively small sample size. Diagnostic tests confirm no serial correlation, heteroskedasticity, or non-normality issues, validating the robustness of the BVAR framework. Lag order selection was determined using multiple criteria, with the VAR Lag Order Selection Criteria favouring a lag of 1 ensuring a model given the small sample from 2000 to 2020.

Table No.3 : Robustness Checks for BVAR Model (2000–2020)

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	**0.979678**	**Prob. F(2, 11)**	**0.4059**
Obs*R-squared	**3.175039**	**Prob. Chi-Square(2)**	**0.2044**

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.95009	Prob. F(7, 13)	0.1416
Obs*R-squared	10.75634	Prob. Chi-Square(7)	0.1496
Scaled explained SS	3.654131	Prob. Chi-Square(7)	0.8186

VAR Lag Order Selection Criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	214.3242	NA	1.51E-19	-20.6324	-20.2341	-20.5547
1	402.8065	207.3304*	1.03e-24*	-33.08065*	-29.49601*	-32.38089*

Normality Test	
Jarque Bera	0.048142
Probability	0.976217

Source: Secondary Data-author computed

Table No.4 : Forecasted Values of Key Variables for India (2021–2027)

FORECASTED YEAR	REC	CO2	RD	PM 2.5	ET	LR	FDI	GDP Deflator
2021	1.539	1.700	0.652	3.841	1.390	2.217	1.704	2.827
2022	1.531	1.729	0.654	3.844	1.432	2.269	1.705	2.916
2023	1.525	1.757	0.651	3.849	1.455	2.243	1.704	2.938
2024	1.520	1.782	0.647	3.855	1.471	2.228	1.703	2.912
2025	1.516	1.804	0.643	3.860	1.483	2.218	1.703	2.836
2026	1.512	1.824	0.639	3.866	1.491	2.216	1.702	2.739
2027	1.510	1.842	0.635	3.872	1.498	2.218	1.701	2.633

Source: Secondary Data-author computed

The forecasted data for 2021–2027 reveals a gradual increase in Renewable Energy Consumption (REC), from 1.539 in 2021 to 1.510 in 2027, indicating a very slight declining trend. This suggests that while renewable energy remains a key part of the energy mix, its growth rate is slowing, likely due to structural constraints or policy inertia. CO2 Emissions show a steady increase (1.700 to 1.842), implying rising fossil fuel use or industrial activity. This contradicts the declining REC, reinforcing the earlier VAR analysis that higher CO2 levels negatively impact renewable adoption. R&D Expenditure (RD) exhibits a gradual decline from 0.652 to 0.635, which may suggest weak prioritization of innovation in green technologies. Given the negative effect of RD on REC in the short term (as per IRFs), this trend could reflect delayed returns on renewable-focused research. PM2.5 Pollution marginally rises from 3.841 to 3.872, showing persistent air quality concerns. Despite this, REC remains flat, implying pollution-induced urgency is not translating into cleaner energy adoption, possibly due to policy gaps.

Environmental Trade (ET) increases modestly (1.390 to 1.498), which may help in transferring green tech, but its initial negative effect on REC suggests this growth must be carefully managed to avoid displacing local renewables. Labour Force Participation (LR) remains fairly stable (~ 2.21–2.27), indicating a neutral influence on REC as confirmed by the VAR results. FDI stays almost constant (~ 1.70), showing no significant scaling in foreign green investments, which aligns with the weak and mixed impact FDI has on REC. GDP Deflator (Inflation proxy) shows a mild declining trend from 2.827 to 2.633 after peaking in 2023, suggesting easing inflation pressures. However, as the VAR showed limited inflation impact, this may not strongly influence REC.

VI. CONCLUSION

This study employed a Bayesian Vector Autoregression (BVAR) framework to analyse and forecast India's macroeconomic and environmental indicators from 2021 to 2027. Utilizing historical data from 2000 to 2020, the research investigates the dynamic interactions between renewable energy consumption (REC), CO_2 emissions, PM2.5 pollution, foreign direct investment (FDI), R&D expenditure, labour force participation, inflation, and environmental trade. This study builds on Bayesian time-series foundations and sustainability transition frameworks widely used in macro-environmental analysis (Litterman, 1986; Pesaran & Shin, 1998; IMF, 2024; Lin et al., 2024; Qureshi et al., 2024). The BVAR model allows for robust forecasting under uncertainty and provides insights into the lagged effects and interdependencies among these variables, offering valuable guidance for policymakers aiming to align economic growth with environmental sustainability.

The estimation results reveal that Renewable Energy Consumption in India exhibits strong path dependency, indicating that past levels significantly influence current trends. This underscores the importance of consistent policy support and long-term planning in the energy sector. However, environmental stressors such as rising CO_2 and PM2.5 emissions are found to negatively affect REC, challenging the assumption that increasing pollution naturally accelerates green energy adoption. Foreign Direct Investment shows transitional dynamics initially suppressing renewable energy use before turning mildly positive, suggesting that FDI inflows may not be effectively aligned with clean energy goals without targeted interventions.

This aligns with Aguirre and Ibikunle (2014)'s global finding that FDI drives renewable growth via technology transfer, but their panel approach missed the initial suppression we observe, likely due to India's fossil-fuel dominance. Similarly, the strong path dependency in REC (coefficient 0.427971) echoes Dogan and Seker (2018)'s long-term EU trends, though our BVAR adds granularity with lagged effects absent in their cointegration model.

Impulse response analysis further uncovers counterintuitive effects: environmental trade and R&D initially suppress REC, reflecting possible misalignments in current policy frameworks. Meanwhile, inflation exhibits a transitional impact, reinforcing the need for macroeconomic stability to support long-term green investments. This counterintuitive suppression by R&D and environmental trade mirrors Shahbaz et al. (2024)'s BRICS findings on governance misalignments, but our BVAR extends this by quantifying dynamic lags, unlike their static panel approach. The transitional inflation impact contrasts with Ozturk and Saboori (2021)'s U.S. study, where policy stability consistently boosted REC, highlighting India's unique macroeconomic volatility.

Forecasting results indicate a stagnation in REC growth over the next decade, despite rising emissions and declining R&D expenditure. This trend highlights structural bottlenecks that could hinder India's progress toward its Viksit Bharat 2047 vision and climate commitments under the Paris Agreement. The forecasted stagnation in REC (1.539% to 1.510% by 2027) diverges from Dogan and Seker (2018)'s EU projection of 2–3% annual growth, reflecting structural bottlenecks in India not captured by their cointegration framework. Rising CO_2 amid declining R&D aligns with Hoang et al. (2024)'s bidirectional causalities, but our IRFs reveal PM2.5's overlooked drag, absent in their time-series model, while Liu et al. (2023)'s BRI analysis of trade-FDI inertia supports our flat REC trend, though our BVAR's dynamic forecasting offers a sharper India-specific lens.

Based on these findings, several policy recommendations arise.

1. Scale R&D with Green Innovation Fund: Allocate 0.5% of GDP annually to a Green Innovation Fund for storage, grid tech, and green hydrogen and To offer 25% R&D tax credits to private firms, inspired by Aguirre and Ibikunle (2014), to fast-track commercialization by 2035.
2. Smart Environmental Trade Policies: Protect domestic renewable industries with targeted tariffs while securing global tech via joint ventures. A Green Tech Import Framework (Liu et al., 2023) can prioritize low-carbon equipment with duty exemptions.
3. Pollution-Triggered Policy Response: Implement subsidies for renewables in high-emission sectors when AQI exceeds 150. Use AI-driven public campaigns (Zhao et al., 2024) to link air quality to energy choices, boosting social demand by 2030.
4. Stabilize Green Financing: Align green lending rates with inflation (1–2% above), as per Shahbaz et al. (2024). Issue 10-year inflation-indexed green bonds to reduce investor risk, leveraging for macroeconomic stability.
5. Channel FDI to Green Sectors: Offer tax holidays for FDI in solar, wind, and green hydrogen, targeting $30 billion by 2032 (Cui et al., 2023). Use blended finance tools to de-risk investments in futuristic grid-scale storage.
6. National Renewable Transition Council: Establish an NRTC to align energy, environment, and trade policies, using AI dashboards for real-time monitoring. Annual progress reports, aligned with IMF (2024), will ensure global benchmarking.

In conclusion, this study highlights the complex non-linear dynamics shaping India's energy transition. While challenges remain, strategic reforms in regulation, finance, innovation, and governance can enable India to achieve both economic growth and environmental sustainability. Without timely action, the country risks locking itself into an unsustainable development path. The insights presented here offer a roadmap for policymakers to navigate India's evolving energy landscape and fulfil its global climate commitments.

Declarations

Generative AI tools were used solely for language editing and formatting purposes. They were not used for conceptual development, data analysis, or interpretation. The authors take full responsibility for the content of this manuscript.

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Ethics Declaration -**Not applicable**. This study does not involve human participants, animals, or clinical data.

Consent to Participate - **Not applicable**. This study does not involve human participants.

Consent to Publish - Not applicable. This manuscript does not contain any individual person's data in any form.

Clinical Trial Registration - Not applicable. This study is not a clinical trial.

Author Contribution

The author declares no conflicts of interest financial or non-financial related to the content of this manuscript. Generative AI tools were used solely for language editing and formatting and not for conceptual development, analysis, or interpretation. The author reviewed and verified all content and assumes full responsibility for the manuscript.

Data Availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request. The data were obtained from publicly accessible secondary sources including the World Bank, International Energy Agency, and Reserve Bank of India.

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Figures

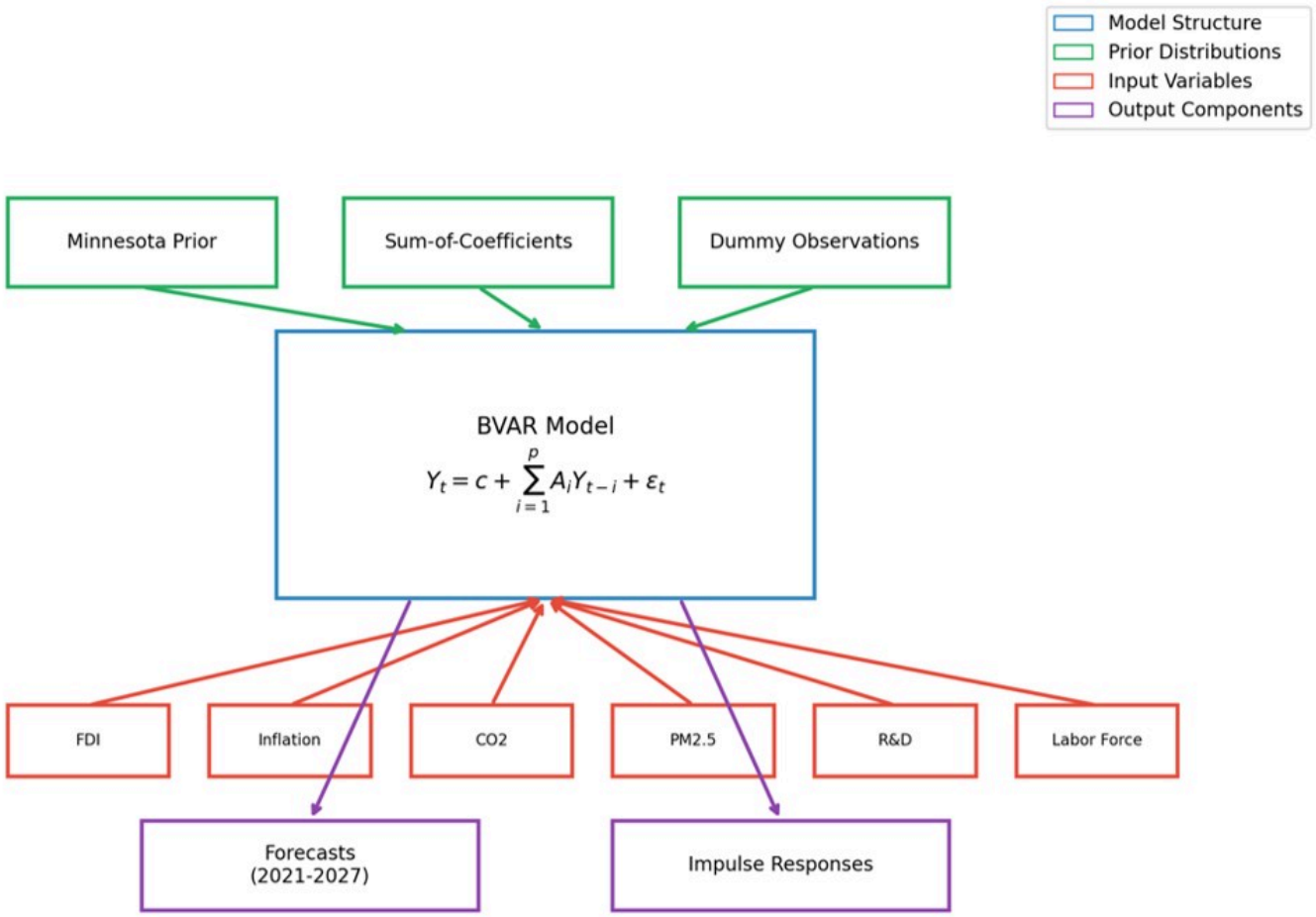
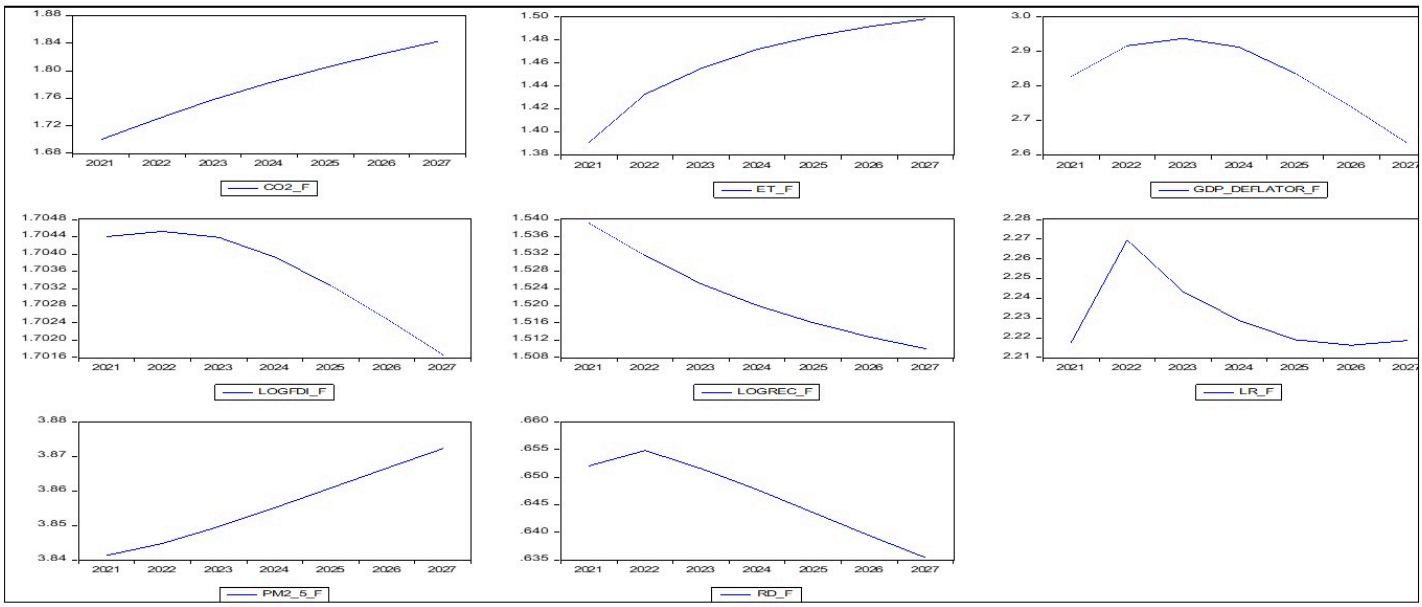


Figure 1

Architectural Framework of the BVAR Model



Source: Secondary Data-author computed

Figure 2

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