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Deagriculturalisation and India's trajectory toward net-zero: Analysing emission impacts using bayesian vector autoregression

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ABSTRACT

This study examined how deagriculturalisation has impacted CO_2 emissions in India from 1990–2023. Although structural economic change is often seen as a sign of progress, little is known about how it affects the environment, especially in large emerging economies experiencing rapid urban and industrial growth. Using a Bayesian Vector Autoregression model with Minnesota priors, we estimated both short-term and long-term emission responses to the contraction of the agricultural sector in 2025. Our findings showed that a 1% decrease in agriculture's GDP share led to an immediate 0.22% increase in CO_2 emissions, which accumulated to 1.5% over ten years. This ongoing rise resulted from land-use changes, coal-intensive industrialisation, and urban sprawl that displaced carbon-absorbing croplands. Impulse response functions showed asymmetric dynamics: declines in agriculture drive emissions more strongly than growth reduces them. Energy consumption and industrialisation were the primary drivers of emissions, while high-tech exports offered only minor decarbonisation benefits. These results challenged the idea that sectoral diversification automatically supports climate goals. To reach India's Net Zero 2070 target, policies need to decouple industrial growth from fossil fuels, such as transforming coal corridors into green hydrogen hubs, and include agroecological zoning to protect carbon-rich agricultural lands. This research provided empirical evidence to fill a key policy gap of how to manage structural change without locking in high emissions.

Keywords: Bayesian VAR model, CO_2 emissions, Deagriculturalisation, Net zero targets

Agriculture is vital to developing economies, providing livelihoods and income security (Dogan 2016, Hu *et al.* 2020, Streimikis and Saraji 2022). In India, it employs about 40% of the workforce and supports socioeconomic stability, rural livelihoods, and food security (Padalia *et al.* 2017, IBEF 2024). India is a major player in global agri-food, leading in milk, pulses, and spices, and ranking second in fruits, vegetables, wheat, and rice (Padalia *et al.* 2017, IBEF 2024). However, environmental pressures are rising. In 2023, India was among the six largest greenhouse gas emitters, producing over 60% of global fossil fuel use and GHG emissions alongside the US, China, the Europe, Brazil, and Russia (Crippa *et al.* 2024).

India's energy future highlights a dilemma. With over 1.4 billion people and strong economic growth, it's the world's fastest-growing major energy market. Electricity use jumped from 874 billion units in 2013–14 to 1,543 billion in 2023–24, growing at an annual rate of 5.8%. Industry is the main energy user, making up nearly half of total energy and 40% of electricity. Renewable energy progress is notable, but coal still dominates industrial production, dropping only from 70% to 63% in a decade. Transport accounts for about 12% of final energy, adding pressure and increasing emissions (BEE 2024).

Recent World Energy Outlook 2025 projections highlight ongoing challenges. India will see the largest increase in global energy demand through 2035, surpassing China, with demand rising about 3% annually. Investment shifts toward renewables, with non-fossil-to-fossil power investment rising from parity in 2015 to nearly 4:1 in 2025. However, coal remains entrenched, especially in industry, which is expected to use over half of all additional energy demand through 2050 (IEA 2025). India's economic transformation has accelerated, with agriculture's share of GDP (Gross domestic product) and employment declining from 61% and 30% in 1991 to 42.86% and 16%, respectively. This shift toward industry and services, linked to rapid urbanisation and fossil fuel-based growth, presents a dilemma: balancing structural economic reallocation with environmental goals, especially its net-zero emissions target by 2070.

Research links structural change to environmental outcomes, with studies in Pakistan and China associating deagriculturalisation with higher CO_2 emissions and uneven growth (Xu and Lin 2017, Ullah *et al.* 2021). Khan *et al.* (2023) highlighted that the impacts of agricultural change evolve with economic development. Most of the literature

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focused on linear relationships, overlooking asymmetric effects in which sectoral decline might disproportionately increase emissions. Lin *et al.* (2022) emphasised regional differences and underscored the need for country-specific analysis.

Despite research on structural change and environmental impacts, key gaps remain. Most studies link deagriculturalisation to CO_2 emissions linearly, missing asymmetric, long-term effects. Evidence mainly comes from China or small economies like Pakistan, limiting relevance to India's unique development. India's shift involves delayed productivity, rapid urbanisation, and a coal-dependent industry within a complex federal system. Few studies explored how agricultural shocks impact emissions in the short and long term. The lack of non-linear, country-specific, dynamic analyses hampers understanding of deagriculturalisation's effects on India's energy, industry, and trade in the context of its emission trends.

This study explored how deagriculturalisation impacts CO_2 emissions in India, using a Bayesian Vector Autoregression with Minnesota priors. The study aimed to measure short- and long-term emission responses to shocks in agriculture's share of GDP; to determine if declines in agriculture cause different emission effects than other macro factors; and to assess deagriculturalisation's role compared to energy, industrialisation, and trade in emission changes.

MATERIALS AND METHODS

The study used annual data for India from 1990–2022. Deagriculturalisation is defined as the decline in agriculture's share of GDP as economies shift toward industry and services. Agricultural value added (% of GDP) directly measures this structural change. Following Ullah *et al.* (2021), who used agricultural value added (% of GDP) as a proxy for deagriculturalisation, we used the same measure in our study. Key variables used in the study included Agr, Agricultural value-added (% of GDP) (as a proxy of deagriculturalisation); EC, Energy consumption (serves as an indicator of the demand for energy within the industrial sector); PD, Population density (an indicator of environmental pressure and resource consumption); TR, Trade % GDP (an indicator of the expansion of industrial and transport activities); EG, Economic growth (an indicator of the overall dynamics of the economy); FD, Financial development (facilitating investment in energy-intensive industries); IN, Industry value added (% of GDP) as industrialisation (the relationship between industrial development and environmental pollution); and HTCH, Export of high-tech products (the impact of innovation on reducing or increasing CO_2 emissions). In this study, the dependent variable is CO_2 emissions, and the remaining variables are independent. The general BVAR model used in this study is as follows:

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{(t-i)} + \varepsilon_t$$

Where Y_t, Vector containing the endogenous variables: CO_2 emissions, agricultural share, energy consumption, population density, trade, economic growth, financial development, industrialisation, and high-tech exports; A_0, Intercept terms; A_i, Coefficient matrices for lagged values of Y_t; ε_t, Error term assumed to be normally distributed.

Macroeconomic and environmental variables, including CO_2 emissions, energy consumption, industrialisation, and sectoral composition, are inherently endogenous because they evolve jointly and influence one another over time. For instance, rising emissions may affect economic growth and energy policy, while economic expansion and structural transformation simultaneously shape emission trajectories. Conventional single-equation or static regression approaches may therefore be subject to simultaneity bias and reverse causality.

The Bayesian Vector Autoregressive (BVAR) model was used to examine the dynamic effects of deagriculturalisation on CO_2 emissions in India in 2025. The Bayesian Vector Autoregression is a statistical tool that analyses how multiple economic variables interact and influence each other over time. Unlike traditional models, BVAR incorporates prior knowledge (historical patterns) to improve accuracy, especially with limited data. Bayesian restrictions in such a model help reduce overfitting and improve forecasting accuracy. This method enables modeling complex, dynamic relationships among variables across short and long time horizons. In vector autoregressive models, large number of parameters leads to biased predictions. Bayesian vector autoregressive techniques produce more reliable forecasts and more accurate estimates of model coefficients by simplifying parameterisation and incorporating prior distributions.

This analysis also used the Minnesota prior, which reduces uncertainty in the estimate. The Minnesota prior assumes that each variable follows a random-walk pattern. This straightforward specification effectively forecasts macroeconomic factors using time-series analysis and is often used as a benchmark for evaluating accuracy (Kuschnig and Vashold 2021). Variance Decomposition (VD) and Impulse Response Functions (IRFs) have also been used to analyse variables over a 10-year horizon.

The BVAR framework mitigates these concerns by treating all variables as jointly endogenous and modeling their dynamic interdependencies in a unified system. By incorporating lagged values of all variables, the BVAR captures feedback effects and temporal causality without imposing restrictive exogeneity assumptions. Furthermore, Minnesota priors reduce parameter uncertainty and overfitting, yielding stable estimates even in relatively small samples. As a result, the BVAR approach provides a robust empirical framework for analysing the dynamic, endogenous relationship between deagriculturalisation and CO_2 emissions in India.

Bayesian constraints (Minnesota Prior) in the BVAR model: To avoid over-fitting, Bayesian Minnesota Prior restrictions are imposed over the model. For instance, Prior Mean (The coefficients of intercepts for the individual variables are taken to have values near one, and for other coefficients near zero), and Prior Variance (The variance of the coefficients of the independent variables is reduced to avoid excessive model complexity). Implementing such priors keeps the BVAR model stable while preserving the underlying relationships in the economy.

Impulse response analysis and variance decomposition: After estimating the BVAR model, the work examined the 10-year-ahead dynamic impact of a 1% one-period negative agricultural share (Agr) shock on CO_2 emissions using IRFs. Variance Decomposition (VD) is then conducted to calculate each variable's contribution to variation in CO_2 emissions.

Conceptual framework: This study's framework explored how structural economic transformation affects environmental outcomes. Deagriculturalisation, indicated by a shrinking share of agriculture in GDP, shows a shift of labour and resources to industry and services. This affects CO_2 emissions directly through land-use change and urban growth, and indirectly through higher energy use, industrial production, and trade. Energy use and industrialisation are key channels, with economic growth, population density, financial development, and trade openness influencing their impact. Feedback mechanisms also exist, where rising emissions can affect policies, investments, and sectors. The Bayesian VAR model captures these interactions by treating all variables as jointly endogenous, allowing dynamic feedback over time.

RESULTS AND DISCUSSION

Table 1 shows that the mean annual GDP growth (EG) was 6.06%, with a standard deviation of 2.84. The average CO_2 emissions were approximately 1,475,500 kg tonnes, with high variability (std. dev. 715,293). Agricultural value-added (Agr) averaged 19.92% of GDP, while energy use per capita (EC) averages 514.95 kg of oil equivalent. Trade openness (TR), financial development (FD), high-tech exports (HTCH), industrial value-added (IN), and population density (PD) had mean values of 36.43%, 39.31%, 9.47%, 27.78%, and 391.15 people/km^2, respectively.

Unit root tests (Augmented Dickey-Fuller): The tests indicated that economic growth, financial development, and high-tech exports were stationary at the level (Table 2). In contrast, CO_2 emissions, agricultural value-added, energy use, population density, trade openness, and industrialisation were non-stationary at the level but became stationary after first differencing, as indicated by statistical significance (p<0.01). The stationarity tests confirmed the integration properties of the variables, justifying the use of a BVAR model in first differences to avoid spurious regression and enable valid inference about long-run relationships.

To build a solid understanding of the relationships, we explored by looking at the simple pairwise connections before diving into the more complex analysis. This step helps

Table 1 Definition and descriptive statistics of the variables

Symbol	Definitions	Mean	Standard deviation	Sources
EG	GDP growth (annual %)	6.06	2.84	World Bank
CO_2	Carbon dioxide emissions (Kilotons)	1475500	715293	World Bank
Agr	Agricultural value-added constant (% of GDP)	19.92	4.09	World Bank
TR	Trade (% GDP)	36.43	12.47	World Bank
EC	Measured as energy use in kg of oil equivalent per capita	514.95	129.42	World Bank
FD	Domestic credit to the private sector (% of GDP)	39.31	12.16	World Bank
HTCH	High-tech exports	9.47	2.04	World Bank
IN	Industry (including construction), value added (% of GDP)	27.78	1.80	World Bank
PD	Population density	391.15	57.51	World Bank

Table 2 Unit root test results

Variable	ADF statistic	p value	Stationary (Level)	ADF statistic	p value	Stationary (1st Diff)
CO_2	-1.98	0.29	No	-5.12***	0.000	Yes
Agr	-2.15	0.23	No	-4.87***	0.000	Yes
EC	-1.75	0.40	No	-4.32***	0.001	Yes
PD	-1.53	0.51	No	-3.94***	0.003	Yes
TR	-2.01	0.28	No	-4.65***	0.000	Yes
EG	-3.42*	0.01	Yes	—	—	—
FD	-3.10*	0.03	Yes	—	—	—
IN	-1.89	0.34	No	-3.88***	0.004	Yes
HTCH	-2.97*	0.04	Yes	—	—	—

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Agr, Agricultural value-added (% of GDP); EC, Energy consumption; PD, Population density; TR, Trade % GDP; EG, Economic growth; FD, Financial development; IN, Industry value added (% of GDP); HTCH, Export of high-tech products.

us get a first impression of how the core variables relate to each other and whether their signs match our expectations based on theory. We found that energy use had the strongest positive link to CO_2 emissions, which makes sense. The positive relationship with deagriculturalisation supports the idea that economic changes are connected to environmental impacts. Interestingly, the negative correlation with high-tech exports was a positive sign that encourages further investigation in more detailed models.

Determining the appropriate temporal lag structure was a critical pre-requisite for specifying a robust time-series model, we therefore, employed a suite of standard information criteria—the Akaike, Schwarz, and Hannan-Quinn criteria—to objectively identify the optimal lag length that captures relevant dynamics without overfitting. The criteria unanimously selected a lag of one. To ensure the robustness of this specification, we estimated alternative models with longer lags, finding they introduced overparameterisation without altering the fundamental conclusions drawn from the impulse response analysis. Consequently, the parsimonious one-lag model was retained for all subsequent estimations.

The BVAR analysis results revealed key insights (Table 3). The positive coefficient for deagriculturalisation indicated that a 1% decline in agriculture's GDP share was associated with a 0.22% rise in CO_2 emissions, consistent with studies on structural shifts toward energy-intensive sectors (Ullah *et al.* 2021, Lin *et al.* 2022). India's urbanisation efforts, like the National Smart Cities Mission and the Delhi-Mumbai Industrial Corridor, further drive land-use change and industrial growth (Bajpai and Biberman 2021).

Second, energy consumption was the most potent driver, with a 1% increase in EC associated with a 0.42% increase in emissions, underscoring the dominant role of fossil fuel dependence (Zou and Zhang 2020, Gibba *et al.* 2024). This underscores the critical importance of India's ambitious targets to achieve 450–500 GW of renewable energy capacity by 2030–2035. Such a transition is pivotal not only for emission reduction but also for enhancing energy security and geopolitical standing (Villanthenkodath and Pal 2024).

Table 3 Bayesian VAR analysis for CO_2 emissions in India

Independent variable	Coefficient	Std. Error	t-statistic	Probability
Agr	0.22	0.15	5.67	0.000
EC	0.42	0.10	9.20	0.000
PD	0.12	0.05	2.40	0.017
TR	0.21	0.08	3.88	0.000
EG	0.18	0.09	2.00	0.046
FD	0.09	0.07	1.29	0.198
IN	0.38	0.12	3.75	0.000
HTCH	-0.06	0.04	-1.50	0.135

Agr, Agricultural value-added (% of GDP); EC, Energy consumption; PD, Population density; TR, Trade % GDP; EG, Economic growth; FD, Financial development; IN, Industry value added (% of GDP); HTCH, Export of high-tech products.

Third, population density and economic growth made significant positive contributions to emissions, consistent with patterns observed in other developing economies (Dwivedi and Soni 2023, Rao 2023, El Weriemmi and Bakari 2024). Urban concentration increases demand for energy, transportation, and infrastructure, while economic expansion traditionally fuels industrial activity. However, India's future trajectory might decouple growth from emissions as its renewable energy mix expands substantially (Dasgupta and Sarangi 2021).

Fourth, trade openness and industrialisation were confirmed as significant drivers of emissions, linked to increased manufacturing, transportation, and energy-intensive production (Shahzad *et al.* 2017, Dou *et al.* 2021, Patel and Mehta 2023). The strong effect of industrialisation, particularly in sectors such as steel and cement, was compounded by a federal governance structure in which state-level policies can sometimes favour coal-dependent industrial pathways.

Finally, the results for financial development and high-tech exports were not statistically significant. The non-significant role of FD suggested that, in the Indian context, financial market development has not yet been directly channeled to drive or mitigate emissions, a finding supported by Omri *et al.* (2015) but contrasting with studies from other regions (Zoaka *et al.* 2022). Similarly, although high-tech exports showed a slight negative coefficient, the result was not significant, suggesting that India's IT and software sectors had not yet reached a scale at which their inherently lower carbon footprint substantially offsets emissions from other sectors. The potential of technology and green finance to contribute to decarbonisation might be realised through future policy initiatives, such as the National Hydrogen Mission, which aims to achieve energy independence by 2047.

Impulse Response Functions (IRFs): Effect of deagriculturalisation on CO_2 emissions: To trace the temporal evolution of deagriculturalisation's influence on

Table 4 Impulse response functions results

Period (Years)	Effect on CO_2 emissions (%)	Interpretation
1	+0.5%	Immediate rise due to land-use changes (e.g. deforestation for urbanisation).
3	+0.8%	The cumulative effect of industrial expansion is the replacement of agriculture.
5	+1.2%	Peak impact from fossil fuel-dependent sectors (e.g. manufacturing).
10	+1.5%	Persistent long-term rise due to structural economic shifts.

emissions, a 1% negative shock to agriculture's share of GDP was simulated using a Bayesian VAR model with Minnesota priors (lag = 1).

Impulse-response analysis provides critical insights into the timing, magnitude, and persistence of emissions responses to structural economic shocks, with direct implications for India's policy landscape. The impulse response functions showed how CO_2 emissions respond over a 10-year horizon to a 1% negative shock to agriculture's share of GDP, capturing the environmental consequences of deagriculturalisation in India (Fig. 1, Table 4). The results revealed distinct short-run adjustments and long-run structural responses that can be directly linked to India's evolving development policies.

In the immediate aftermath of the shock, CO_2 emissions rose by approximately 0.5% [Short-run dynamics (Years 1–3)]. This early response reflects rapid land-use conversion and construction activity as agricultural land is reallocated for urban housing and infrastructure. National initiatives such as the Pradhan Mantri Awas Yojana (Urban) and the Smart Cities Mission have accelerated residential construction and urban expansion, particularly in peri-urban regions. These programmes increase demand for carbon-intensive inputs such as cement, steel, and diesel, generating an immediate emissions response even before full-scale industrial activity materialises.

Between the third and fifth years, the emission response intensified, peaking at around 1.2%. During this phase, the dominant transmission channel shifted from land-use change to energy-intensive industrial expansion. Policies under the National Industrial Corridor Programme, including the Delhi–Mumbai Industrial Corridor and related logistics networks, had facilitated the spatial concentration of manufacturing activities. Complementing this, the PM Gati Shakti National Master Plan had expanded freight corridors, highways, and multimodal logistics hubs, significantly increasing fossil fuel consumption in transport and industry. As labour exits agriculture and relocates to these industrial clusters, emissions rise more sharply.

Over the long run (5–10 years), the response stabilises at approximately 1.5%, indicating a persistent, structurally

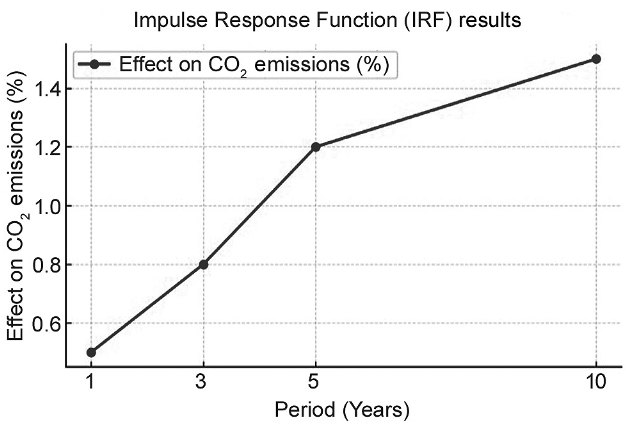

Fig. 1 Effect of deagriculturalisation on CO_2 emissions.

embedded increase in emissions. This persistence reflects carbon lock-in effects from infrastructure investments and industrial incentives under Production-Linked Incentive (PLI) schemes, which promote manufacturing growth without binding emission constraints. Once established, industrial plants, transport corridors, and urban settlements create durable demand for coal-based electricity and fossil fuels. Although renewable energy capacity has expanded, it has not yet been sufficient to offset emissions embedded in these long-lived assets.

Fig. 1 captures this trajectory: a steady, upward-sloping curve that never flattens, underscoring the persistent environmental footprint of deagriculturalisation. It confirmed that India's CO_2 emissions have a significant agricultural component. This conclusion aligns with the IPCC (2019), Udemba *et al.* (2021) and the IEA (2023), which indicated that India's land-use changes, the transition to high energy use (rapid industrial and transportation development driven by agricultural decline), and shifts in its economic structure will contribute to rising CO_2 emissions.

Table 5 summarises the short- and long-term responses of emissions to shocks in key macroeconomic variables over a 10-year period. Energy consumption had the strongest effect, increasing CO_2 emissions by 1.8% in the first three years and by 3.5% in the long run. This persistent effect underscores India's entrenched reliance on coal and other fossil fuels, a structural constraint that must be urgently addressed in the deployment of renewable energy. India is among the top three carbon-emitting countries and is heavily dependent on coal. Thus, the development of renewable energy (solar, wind) is key to addressing this, and strengthening India's National Solar Mission and Renewable Energy Targets is imperative.

Industrialisation followed closely, with a 1.2% short-term and 2.8% decade-long increase in emissions. This reflects the carbon intensity of India's manufacturing and construction sectors, which have expanded under initiatives such as "Make in India" and the PLI schemes, without equivalent safeguards to decarbonise. Similarly, trade openness contributes 0.9% initially and 1.5% over

Table 5 Impulse response functions (other variables)

Variable	Short-term effect (Year 1–3)	Long-term effect (Year 10)
EC	+1.8% ↑ CO_2	+3.5% ↑ CO_2
IN	+1.2% ↑ CO_2	+2.8% ↑ CO_2
TR	+0.9% ↑ CO_2	+1.5% ↑ CO_2
PD	+0.3% ↑ CO_2	+0.7% ↑ CO_2
EG	+0.6% ↑ CO_2	+1.0% ↑ CO_2
FD	+0.4% ↑ CO_2	+0.8% ↑ CO_2
HTCH	-0.2% ↓ CO_2	-0.5% ↓ CO_2

EC, Energy consumption; PD, Population density; TR, Trade % GDP; EG, Economic growth; FD, Financial development; IN, Industry value added (% of GDP); HTCH, Export of high-tech products.

time, driven by logistics and export-oriented production in energy-intensive industries such as textiles, chemicals, automobiles, and steel.

Population density and economic growth had small yet cumulative effects, 0.3–0.7% and 0.6–1.0%, linked to urban energy demand and infrastructure growth. India's urban population is expected to reach 675 million by 2035, up from 483 million in 2020, increasing emissions. Strategies like sustainable urban planning, smart cities, public transportation, carbon pricing, emissions trading, and green finance incentives are key to addressing this growth. Financial development also showed a mild but persistent positive association (+0.4 to +0.8%), suggesting that credit flows had historically favoured carbon-intensive investment.

Notably, high-tech exports was the only variable with a modest mitigating effect, reducing emissions by 0.2% in the near term and 0.5% over ten years. This aligns with the lower carbon footprint of India's IT and electronics sectors, though the magnitude suggests limited systemic impact without deeper integration of green innovation into industrial policy.

According to the results, India should prioritise the National Hydrogen Mission, the Faster Adoption and Manufacturing of Electric Vehicles (FAME) programme, and solar expansion. Additionally, India must increase research and development (R&D) investment in green technology to ensure long-term sustainability.

The variance decomposition of CO_2 emissions at one- and ten-year horizons was also interpreted, showing the share of forecast error variance attributable to shocks in each variable (Table 6). In the short run, energy consumption and industrialisation dominated together accounting for over half of the variation in emissions (35% and 18%, respectively). By the tenth year, EC remained the largest single contributor (28%), while IN's share rose to 22%, underscoring the growing influence of industrialisation. Notably, deagriculturalisation also gained traction over time, increasing its share from 12% to 18%. This trend highlights that the structural shift away from agriculture is not merely an economic transition but also a growing source of environmental pressure. In contrast, financial development, high-tech exports, and economic growth played minor roles, each contributing 9% or less, and EG declined slightly over the decade.

Collectively, these dynamic results suggest that India's current development pathway, if unaltered, risks locking in high-emission infrastructure. Achieving its Net Zero 2070 goal requires policy measures that actively steer structural transformation. This entails aligning industrial and urban development policies (such as PLI and Smart cities) with low-carbon transitions, significantly scaling up renewable energy and green hydrogen missions, and embedding decarbonisation criteria in trade and financial systems. The minor roles of financial development and high-tech exports in the variance decomposition further suggest that channeling finance and innovation specifically toward green technologies should be a targeted priority. Ultimately, managing India's growth story requires actively steering this economic transition with green innovation and targeted finance, lest short-term gains imperil its long-term climate goals. Without policies to decouple structural transformation from emissions-intensive pathways, India risks locking in emissions that threaten its Net Zero 2070 goal. Structural change must be guided rather than left to chance.

Table 6 Variance decomposition of CO_2

Period	EC	IN	TR	Agr	PD	EG	FD	HTCH
1	35%	18%	10%	12%	5%	8%	7%	5%
10	28%	22%	12%	18%	6%	9%	5%	3%

Agr, Agricultural value-added (% of GDP); EC, Energy consumption; PD, Population density; TR, Trade % GDP; EG, Economic growth; FD, Financial development; IN, Industry value added (% of GDP); HTCH, Export of high-tech products.

This study showed that deagriculturalisation in India exerts persistent upward pressure on CO_2 emissions, with effects that intensify over time rather than dissipate. The results indicated that energy consumption and industrialisation remain the dominant drivers of emissions, while structural shifts away from agriculture increasingly reinforce long-run carbon lock-in. These findings challenge the assumption that sectoral transformation inherently supports environmental sustainability. Critical interventions must include the strategic development of green hydrogen corridors to decarbonise heavy industry and a national agroecological zoning framework to preserve carbon-sequestering landscapes. Furthermore, aligning industrial policy incentives, such as the Production-Linked Incentive schemes, with stringent emission-reduction benchmarks is essential. Achieving India's Net Zero 2070 target will therefore require aligning structural change with low-carbon energy transitions and land-use planning, rather than allowing economic reallocation to proceed without climate safeguards.

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