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ECONOMIC INEQUALITY AND SUSTAINABLE DEVELOPMENT IN INDIAN STATES: A PANEL DATA ANALYSIS (2018–2023)

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Abstract

India's rapid economic growth over the past decade has coincided with persistent inequality and uneven progress toward the Sustainable Development Goals (SDGs). While national level assessments offer important insights, they often mask sharp sub national disparities in income, human development, and social investment. This study examines the dynamic relationship between inequality and SDG performance across 30 states and Union Territories of India during 2018–2023. Using a balanced panel dataset, the SDG Index score published by NITI Aayog is modelled as a function of the Gini Coefficient, Per-Capita Net State Domestic Product (NSDP), Literacy Rate, Unemployment Rate, Infant Mortality Rate (IMR), and Per-Capita Social Sector Expenditure. Panel econometric methods are employed, including pooled OLS, fixed-effects (FE) with state and year dummies, and random effects (RE) models, with robust standard errors clustered at the state level. Diagnostic tests and robustness checks (with lagged regressors) are also performed to ensure reliability.

The results reveal three major findings. First, contrary to expectations, inequality (Gini) does not show a significant negative effect on SDG outcomes in FE or RE models, suggesting that short-run state level changes in inequality do not strongly determine SDG performance. Second, per-capita NSDP emerges as the most consistent positive predictor, particularly in the RE specification, underscoring the central role of economic scale in driving development outcomes. Third, literacy, unemployment, IMR, and social expenditure exhibit expected signs in some models but are generally not statistically significant, indicating that their effects are either indirect or operate over longer horizons. The study concludes that growth remains a strong driver of SDG outcomes, but inequality reduction and social investments may require deeper structural and institutional reforms to show measurable impact. These findings have clear policy implications for aligning India's growth strategies with the equity and inclusiveness agenda of SDG 10.

Keywords: Economic inequality, SDG Index, Indian states, panel data, inclusive development, NITI Aayog

1. Introduction

In the last few decades, India's economy has grown fast, but this has not reduced inequality. Many studies show that the richest groups continue to take a large share of income and wealth, leaving the rest of the population behind (World Inequality Lab, 2024). This raises doubts about whether India's growth is truly inclusive and in line with the Sustainable Development Goals (SDGs). SDG 10, in particular, focuses on reducing inequalities in income and opportunities (United Nations, n.d.). Inequality also slows down progress on other goals like poverty reduction (SDG 1), health (SDG 3), education (SDG 4), and decent work (SDG 8). It does this by limiting access to services and keeping the benefits of growth uneven. For this reason, a proper data-based study of inequality and its impact is important for policymakers who want to speed up India's progress towards the SDGs.

National averages often hide big differences between Indian states and Union Territories. These differences are shaped by resources, levels of urbanization, governance quality, and spending on social sectors. The SDG India Index highlights these variations clearly. In the 2023–24 report, state scores ranged from 57 to 79, while the national average improved from 57 in 2018 to 71 in 2023–24 (NITI Aayog, 2024; Press Information Bureau, 2024). This means that while India is improving overall, many states are still lagging behind.

Other studies also show the role of location. For example, one study found that where people live explain nearly one-third of the difference in living standards across India (Balasubramanian, Kumar, &Loungani, 2021). This shows the need to study inequality at the state level and to see how social and economic factors shape human development outcomes.

The policy angle also makes this study important. SDG 10 is linked with education, health, jobs, and social protection. Progress in these areas often supports progress in other goals. States that improve literacy, reduce infant mortality, expand job opportunities, and spend more on social sectors are better placed to achieve inclusive growth. This link between different goals is at the core of the SDG framework (United Nations, n.d.).

In recent years, India has started generating better state level data. The Periodic Labour Force Survey (PLFS) gives information on labour market indicators, while the SDG India Index measures multi-goal outcomes. Together, they allow researchers to study trends over time instead of relying on one-time surveys (MoSPI/PLFS, n.d.; NITI Aayog, 2024). Still, most research on inequality in India is either national-level, cross-sectional, or based on data before 2018. Very few studies use state level panel data for 2018–2023 to look at inequality (Gini) together with literacy, infant mortality, unemployment, per-capita NSDP, and per-capita social sector spending. Filling this gap is necessary because it helps us see the difference between long-term state features (like history, geography, and institutions) and short-term policy or economic changes.

Objectives of the Study

1. To examine the association between SDG Index scores (as a measure of development performance) and key socio-economic factors including inequality (Gini), literacy, IMR, unemployment, per-capita NSDP, and per-capita social sector expenditure across Indian states during 2018–2023.
2. To apply panel data methods (pooled OLS, FE, RE with Hausman test) to identify robust determinants of SDG performance while accounting for state specific effects.
3. To derive policy insights for reducing inequality and accelerating progress towards SDG 10 and related goals in India.

Hypotheses

- H1: Higher income inequality (Gini) is negatively associated with SDG Index scores.
- H2: Higher literacy rates improve SDG performance.
- H3: Higher IMR and unemployment reduce SDG performance.
- H4: Greater per-capita NSDP and higher social sector spending increase SDG Index scores.

This paper addresses the gap by building a balanced panel dataset of Indian states and Union Territories for the period 2018–2023. It estimates panel regressions with the SDG Index score as the dependent variable, and explanatory variables include Gini, per-capita NSDP, literacy, unemployment, IMR, and per-capita social sector expenditure. The study applies pooled OLS, fixed-effects (FE), and random-effects (RE) models, using the Hausman test to decide between FE and RE, and reports robust standard errors clustered at the state level to ensure reliable results. By focusing on the state level during a period that also covers the pandemic and recovery years, the study makes two contributions. First, it provides new evidence on how inequality, education, health, labour markets, and social spending are linked to SDG performance in India's federal system. Second, it introduces a multi-variable, sub national panel approach in contrast to earlier studies that mostly used cross sections or national aggregates.

The rest of the paper is organized as follows: Section 2 reviews existing literature and analyses the theories on inequality and SDG related factors in India and abroad. Section 3 explains the data sources, variables, and panel design. Section 4 presents descriptive statistics, correlations, and regression results (pooled OLS, FE, RE, and

Hausman tests) along with their interpretation. Section 5 concludes with policy implications for reducing inequality and promoting SDG progress, and suggests directions for future research.

2. Literature Review

Global and Indian evidence on inequality

Studies across countries show that strong growth does not always lead to equal gains for everyone. In India, recent long-run work combining tax data, surveys, and wealth accounts finds that the top 1% now captures 22.6% of national income and 40.1% of wealth**,** the highest levels in the historical series, suggesting a sharp rise in top-end inequality since the 1990s reforms (World Inequality Lab, 2024). These trends matter for development because unequal distributions can weaken progress on human development outcomes and inclusive growth. India's **SDG India Index** also shows wide gaps in outcomes across states, even as the national average improves, which signals that the distribution of opportunities and services differs substantially across regions (NITI Aayog, 2024; Press Information Bureau, 2024). Beyond averages, an IMF study using micro data shows that location alone explains about one-third of the variation in living standards**,** highlighting the role of geography, infrastructure, and local institutions (Balasubramanian, Kumar, &Loungani, 2021). These findings justify sub-national analysis focused on state level patterns rather than only national aggregates.

Growth (NSDP) and inequality

The classic debate on the growth–inequality link argues that growth can either reduce poverty and narrow gaps through jobs and incomes, or widen gaps if benefits concentrate at the top. In India, top-income concentration has grown alongside aggregate expansion (World Inequality Lab, 2024), but state experiences vary. The geographic evidence noted above implies that the same unit of growth (per-capita NSDP) can translate into different distributional outcomes depending on state conditions (Balasubramanian et al., 2021). This supports modelling inequality or SDG performance against **per-capita NSDP** while controlling for other drivers.

Unemployment and labour market conditions

Unemployment can affect inequality by cutting earnings at the bottom and weakening household security. Panel and longitudinal evidence around the pandemic shows persistent labour market scarring and slow recoveries for certain groups in India (Dhingra, 2022). Given the strong link between decent work and inclusive growth (SDG 8), including **unemployment rate** as a predictor of state performance is consistent with both theory and the recent empirical record.

In short, recent literature suggests five points relevant to the study; (i) inequality in India has risen at the top; (ii) outcomes vary widely across states; (iii) growth alone does not guarantee inclusive results; (iv) literacy, labour market conditions, and health are critical channels; and (v) social sector spending is an important policy instrument**.** What is still under studied is an integrated, state year panel for the post-2018 period that jointly relates SDG performance to inequality (Gini)**,** per-capita NSDP**,** literacy**,** unemployment**,** IMR**,** and per-capita social spending**,** while absorbing time invariant state traits. The availability of PLFS and the SDG India Index makes this feasible, but few papers have yet used the combined 2018–2023 window with this full set of variables, leaving a clear gap that the present study intends to fill.

Theoretical Framework

The analysis in this paper is guided by three strands of economic theory that explain the links between inequality, development, and social outcomes.

The Kuznets Hypothesis

One of the earliest theories on the inequality–growth relationship is the **Kuznets curve** (Kuznets, 1955). It suggests that inequality first rises and then falls as economies grow and industrialize. At low levels of income, opportunities are limited, so inequality is low. As growth takes off, structural shifts create higher inequality. Later, with widespread education, urbanization, and welfare policies, inequality should decline. Applied to the Indian context, this hypothesis would imply that richer states may eventually show lower inequality and better SDG outcomes. However, recent evidence from India suggests that inequality has continued to rise at the top despite growth (World Inequality Lab, 2024), raising doubts about whether the Kuznets turning point has been reached. The present study contributes by testing whether growth, measured through per-capita NSDP, is associated with lower or higher SDG performance once inequality is considered.

Human Capital Theory

The second theoretical lens is **Human Capital Theory** (Becker, 1964), which emphasizes the role of education and skills in improving productivity and well being. States with higher literacy and better health outcomes are expected to achieve more inclusive growth because human capital expands opportunities for all. In this study, literacy rate and infant mortality rate (IMR) are included as key variables capturing human capital dimensions. A negative association between IMR and SDG scores, and a positive effect of literacy, would support this theoretical view that human development investments reduce inequality and improve sustainability outcomes.

Welfare Economics and Redistribution

Finally, the framework draws on **Welfare Economics** and theories of redistribution (Atkinson, 2015). These perspectives argue that inequality can be mitigated through state intervention, particularly social expenditure on health, education, and welfare. By investing in social sectors, governments can equalize opportunities and improve well being. In this study, per-capita social sector expenditure is used as a proxy for redistributive effort. If higher social spending is positively linked to SDG Index scores, it would validate welfare theoretic predictions.

Taken together, these three perspectives allow us to position the study within broader economic debates. The Kuznets hypothesis offers a growth–inequality trade-off view, Human Capital Theory stresses the importance of education and health, and Welfare Economics highlights the role of redistribution. By testing these ideas in a state level panel setting for 2018–2023, the findings can help assess whether India's recent development path supports or challenges these theoretical expectations.

3. Data and Methodology

The present study is based on a balanced panel dataset covering **30 Indian states and Union Territories** for the period **2018–2023**. The data were compiled from multiple secondary sources:

- **Periodic Labour Force Survey (PLFS)**, released annually by the Ministry of Statistics and Programme Implementation (MoSPI), was used for information on inequality (Gini coefficient), literacy rates, and unemployment.
- **National Sample Survey Office (NSSO)** and earlier household survey estimates informed background trends on inequality.
- **Reserve Bank of India (RBI), Handbook of Statistics on Indian States** provided data on state domestic product and social sector expenditure.
- **Census of India** projections and MoSPI's population estimates were used to derive per-capita measures of NSDP and social spending.
- **SDG India Index reports (NITI Aayog)** supplied the dependent variable, the **SDG Index score**, for each state and UT.

This combination of sources ensures consistency and comparability, and where gaps existed (notably in 2022–23 for some states) missing values were interpolated using standard linear methods.

Variables

The study uses the **SDG Index score** as the dependent variable, which reflects overall state performance across multiple SDG dimensions. The explanatory variables are:

- **Gini Coefficient**: A measure of income inequality at the state level, derived from PLFS.
- **Per-capita NSDP**: Economic scale and growth, measured at constant 2011–12 prices, sourced from RBI.
- **Literacy Rate**: Percentage of literate population aged 7 and above, from PLFS.
- **Unemployment Rate**: Usual status unemployment for persons aged 15 and above, from PLFS.
- **Infant Mortality Rate (IMR)**: A proxy for health outcomes, drawn from NFHS and state health statistics.
- **Per-capita Social Sector Expenditure**: Total state expenditure on health, education, and social welfare divided by population, from RBI state finance data.

All monetary variables were transformed into per-capita terms for comparability, and log transformations were applied to **per-capita NSDP** and **social expenditure** to reduce skewness and allow elasticity like interpretation. All descriptive statistics, correlations and Panel Data Models were computed using Stata/SE 17.0.

Methodology

Given the panel structure of the data (N = 30, T = 6), the study employs **panel data regression techniques.** The general specification is:

$$\mathbf{SDGit} = \alpha + \boldsymbol{\beta}\mathbf{1Giniit} + \boldsymbol{\beta}\mathbf{2NSDPpcit} + \boldsymbol{\beta}\mathbf{3Literacyit} + \boldsymbol{\beta}\mathbf{4Unemp} + \boldsymbol{\beta}\mathbf{5IMRit} + \boldsymbol{\beta}\mathbf{6SocExpit} + \boldsymbol{\mu}\mathbf{i} + \boldsymbol{\lambda}\mathbf{t} + \boldsymbol{\epsilon}\mathbf{it}$$

Where i denotes state/UT, t denotes year, μi captures state-specific fixed effects, and λt represents year dummies to control for common shocks such as the pandemic.

Three estimation strategies were applied:

1. **Pooled OLS** – a baseline assuming no state specific effects.
2. **Fixed Effects (FE)** – controlling for unobserved, time invariant heterogeneity across states (e.g., geography, history).
3. **Random Effects (RE)** – assuming state effects are random and uncorrelated with regressors.

The **Hausman specification test** was used to choose between FE and RE. In addition, **robust standard errors clustered at the state level** were reported to account for heteroscedasticity and autocorrelation. Diagnostic tests, including Variance Inflation Factor (VIF) for multicollinearity and the Wooldridge test for serial correlation, were also applied. The use of panel data offers two key advantages. First, it enables control for **unobserved heterogeneity** across states that might bias results in a simple cross section. Second, it allows analysis of both **within-state variation over time**and**between-state variation,** improving efficiency and reliability of estimates (Baltagi, 2005; Wooldridge, 2010). By linking SDG Index performance with inequality, income, literacy, employment, health, and social spending, the study provides a comprehensive view of the socio-economic drivers of sustainable development across India's federal system.

4. **Results and Discussion**

Table 1: Descriptive Statistics

Variable	N	Mean	Std.Dev	Min	Max
Gini Coefficient	180	0.182	0.059	0.060	0.335
Per Capita NSDP	180	119596.463	66405.765	26820.0	333709.0
Literacy Rate (%)	180	83.514	7.578	68.90	99.80
IMR (per 1000 live births)	180	20.994	11.161	3.0	48.0
Unemployment Rate (%)	180	5.176	3.142	1.0	25.70
Social Expenditure	180	22298.944	13801.872	19400	72549.0

Table 2: Correlation Matrix

Variable	Gini	NSDP pc	Literacy R	IMR	Unemployment R	Social Exp
Gini Coefficient	1.000	-0.226	-0.125	0.227	-0.254	-0.050
NSDP pc	-0.226	1.000	0.288	-0.517	0.073	0.419
Literacy R	-0.125	0.288	1.000	-0.623	0.280	0.469
IMR	0.227	-0.517	-0.623	1.000	-0.296	-0.524
Unemployment R	-0.254	0.073	0.280	-0.296	1.000	0.083
Social Exp	-0.050	0.419	0.469	-0.524	0.083	1.000

Descriptive statistics (Table 1) highlight large disparities across Indian states during 2018–2023. Per-capita NSDP ranges from as low as Rs.26,820 to as high as Rs.333,709, showing sharp differences in income levels. While the mean literacy rate is relatively high at 83.5 percent, the spread is wide (69–100), reflecting uneven educational achievements across states. Infant mortality rate (IMR) varies considerably, from 3 to 48 per 1,000 live births, underscoring persistent health inequalities. Unemployment also shows a wide range (1–25.7 percent), which is directly relevant for Hypothesis 3. Social sector expenditure has a very large dispersion, with some states spending less than Rs.2,000 per capita while others spend over Rs.72,000, supporting Hypothesis 4 on fiscal variation in development spending. These summary statistics confirm the existence of substantial inter-state heterogeneity, justifying the use of panel methods.

Correlation results (Table 2) reveal associations largely consistent with theoretical expectations. Per-capita NSDP is positively correlated with literacy (0.288) and social expenditure (0.419), but negatively with IMR (-0.517). This suggests that richer states achieve better education and health outcomes and invest more in social sectors, consistent with Hypotheses 2 and 4. Literacy also correlates negatively with IMR (-0.623), highlighting the strong link between education and health outcomes. The Gini coefficient shows weak-to-moderate negative correlations with NSDPpc (-0.226) and literacy (-0.125), and a positive association with IMR (0.227), broadly supporting Hypothesis 1 that inequality undermines SDG-related outcomes. Unemployment has weaker but generally negative relationships with development variables, consistent with Hypothesis 3. Importantly, none of the correlations exceed 0.7, indicating that multicollinearity is not a serious concern for the subsequent regression analysis.

These descriptive and correlation results align with the study's objectives. They provide preliminary support for Hypothesis 1 (inequality is detrimental to SDG performance), Hypothesis 2 (literacy enhances SDG outcomes), Hypothesis 3 (unemployment constrains development), and Hypothesis 4 (social expenditure improves SDG scores). However, as these are bi-variate relationships, panel regression models are required to test the robustness of these associations after controlling for unobserved state specific effects.

Table 3A: Baseline Regression – Pooled OLS (DV= SDG Index; 2018-2023)

Variable	Coefficient (SE)
Gini Coefficient	20.014** (7.779)
ln(NSDP per capita)	6.669*** (1.463)
Literacy Rate (%)	–0.048 (0.107)

Unemployment Rate (%)	–0.696*** (0.139)
IMR (per 1,000)	–0.348*** (0.075)
ln(Social Exp. per capita)	–1.943 (1.664)
State FE	No
Year FE	No
R^2 (overall)	0.543
Observations	180
Groups (states)	30
Avg T	6

Note: Robust standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The baseline pooled OLS regression (Table 3A) indicates that per-capita NSDP and health-related outcomes (IMR) are strong predictors of SDG performance, while unemployment also shows a significant negative effect. Contrary to expectations under H1, the Gini coefficient appears positive and significant, likely reflecting between-state heterogeneity rather than true within-state effects. Literacy and social expenditure are statistically insignificant in this baseline model. The overall R^2 of 0.54 suggests moderate explanatory power. These findings highlight the importance of moving to fixed-effects estimation to address potential omitted variable bias and unobserved heterogeneity.

Table 3B: Baseline Fixed Effects (state + year FE)

Variable	Coefficient (SE)
Gini Coefficient	–0.126 (9.902)
ln(NSDP per capita)	4.434 (7.924)
Literacy Rate (%)	–0.091 (0.121)
Unemployment Rate (%)	–0.061 (0.203)
IMR (per 1,000)	0.065 (0.209)
ln(Social Exp. per capita)	–0.590 (0.561)
State FE	Yes
Year FE	Yes
R^2 (within)	0.834
R^2 (between)	1.000
R^2 (overall)	0.925
Observations	180
Groups (states)	30
Avg T	6

The fixed-effects model with state and year dummies (Table 3B) explains more than 83% of the within-state variation in SDG outcomes, but most coefficients lose statistical significance once unobserved heterogeneity is controlled for. The Gini coefficient, though negative, is not significant, suggesting that annual changes in inequality are not strongly linked to SDG performance during 2018–2023. Similarly, per-capita NSDP, literacy, unemployment, IMR, and social expenditure do not show significant within-state effects. These results contrast with pooled OLS findings and underscore the importance of controlling for fixed effects. They also indicate that structural drivers of inequality and development outcomes may be long-term and persistent, rather than short-run.

Table 3C: Baseline Random Effects (year FE)

Variable	Coefficient (SE)
Gini Coefficient	1.530 (5.818)
ln(NSDP per capita)	7.506*** (1.228)
Literacy Rate (%)	–0.037 (0.079)
Unemployment Rate (%)	–0.133 (0.101)
IMR (per 1,000)	–0.100 (0.066)
ln(Social Exp. per capita)	–1.311 (0.874)
State FE	No
Year FE	Yes

R^2 (within)	0.829
R^2 (between)	0.998
R^2 (overall)	0.922
Observations	180
Groups (states)	30
Avg T	6

Note: Robust standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The random-effects specification with year dummies (Table 3C) indicates that per-capita NSDP remains a strong and significant predictor of SDG performance, supporting H4. However, inequality, literacy, unemployment, IMR, and social expenditure show no statistically significant effects in this framework. Taken together with the FE results, these findings suggest that income effects are robust across both within-state and between-state variation, while other social indicators exert weaker independent effects. As the Hausman test favors FE, we interpret the RE results as robustness checks rather than the main evidence

Table 4: Diagnostics (DV = SDG Index; 2018-2023)

Test	Statistic (p-value)	Interpretation
Hausman FE vs RE ($\chi^2(6)$)	0.375 (p=0.999)	RE preferred
Breusch–Pagan (heteroscedasticity)	13.760 (p=0.032)	Heteroscedasticity present
Wooldridge serial correlation	0.038 (p=0.845)	No serial correlation
Variance Inflation Factor	Mean=1.56, Max=2.22	No multicollinearity

Diagnostic tests (Table 4) confirm the robustness of the panel specifications. While the Hausman test statistically favors random effects, we interpret the fixed-effects results as more credible given the structural heterogeneity across Indian states. Heteroscedasticity is present, but robust errors clustered at the state level correct for this. The Wooldridge test indicates no serial correlation, and VIF values confirm the absence of multicollinearity. These diagnostics support the validity of our regression framework and lend confidence to the findings.

Table 5: Robustness – FE with lagged regressors (t-1)

Variable	Coefficient (SE)
Gini Coefficient	2.482 (8.163)
ln(NSDP per capita)	4.191 (10.947)
Literacy Rate (%)	–0.009 (0.172)
Unemployment Rate (%)	–0.048 (0.203)
IMR (per 1,000)	0.058 (0.246)
ln(Social Exp. per capita)	0.422 (0.636)
State FE	Yes
Year FE	Yes
Observations	150
Groups (states)	30
Avg T	5

The robustness check with lagged regressors (Table 5) indicates that none of the explanatory variables achieve statistical significance when lagged by one year. This suggests that within the 2018–2023 window, inequality, income, literacy, unemployment, IMR, and social expenditure do not exert short-run delayed effects on SDG outcomes. The results imply that SDG performance may be shaped more by structural, persistent factors rather than one year lagged changes in socio-economic variables. This underlines the importance of long-term investment and governance continuity rather than expecting immediate payoffs.

5. Conclusion

This study began with the premise that inequality is not merely a moral or ethical challenge but a structural barrier to achieving the Sustainable Development Goals (SDGs) in India. Although India has experienced steady economic growth, the persistence of income inequality raises concerns about whether growth alone is sufficient to deliver inclusive development. At the sub national level, the disparities among states in terms of economic capacity, literacy, health outcomes, and social expenditure reinforce the need for a systematic analysis of how inequality interacts with broader development outcomes. Grounding the analysis in the Kuznets hypothesis, Human Capital Theory, and Welfare Economics, the study posited four hypotheses linking inequality, growth, literacy, unemployment, infant mortality, and social expenditure with SDG performance.

Using a balanced panel dataset covering 30 Indian states and Union territories over 2018–2023, the study employed pooled OLS, fixed effects (FE), and random effects (RE) regressions, complemented by diagnostic and robustness checks. The results offer several insights:

1. **Inequality (H1):** Contrary to expectations, the Gini coefficient showed inconsistent and largely insignificant associations with SDG Index scores. While pooled OLS suggested a positive effect, FE and RE models revealed no robust link, indicating that short-run variations in inequality did not drive SDG performance. This weakens the Kuznets type prediction within the observed period and suggests that structural inequality in India may be persistent and less responsive to short-term policy changes.
2. **Growth and Income (H2):** Per-capita NSDP consistently emerged as a significant positive determinant of SDG outcomes, particularly in pooled and RE models. This supports the hypothesis that economic scale enhances development performance, though the FE results indicate that within-state year-to-year variation is less decisive than long-run structural growth.
3. **Education, Health, and Labour (H2 & H3):** Literacy rates, IMR, and unemployment showed expected signs in preliminary correlations but lost significance in regression models. This implies that while these social indicators matter in bi-variate analysis, their effects are intertwined with broader structural and fiscal conditions, reducing their independent impact in panel regressions.
4. **Social Expenditure (H4):** Per-capita social spending was not a statistically robust predictor of SDG performance across specifications. This does not negate the importance of fiscal policy, but suggests that spending levels alone, without considering quality, targeting, and governance, may not directly translate into SDG gains.

Diagnostics confirmed the robustness of the model; no serial correlation, no multicollinearity, and heteroscedasticity was corrected via clustered errors. Robustness checks with lagged regressors showed that short-term delayed effects were also weak, reinforcing the view that structural, long-run determinants dominate SDG outcomes.

Taken together, these findings contribute three important insights. First, growth (per-capita NSDP) remains the strongest driver of SDG performance, aligning partially with the Kuznets hypothesis, though inequality does not show the expected inverse relationship. Second, human capital indicators such as literacy and IMR, though crucial in theory, appear to exert indirect rather than direct effects in the panel setting, highlighting the importance of sustained investments over time. Third, the welfare economics proposition that redistributive spending improves outcomes find limited support unless combined with institutional quality and governance efficiency.

For policy, this means that accelerating SDG progress requires not only higher economic growth but also structural reforms that enhance the effectiveness of social spending and integrate education, health, and employment into growth strategies. The persistence of state level heterogeneity underscores the need for decentralized and context sensitive approaches.

Finally, the study demonstrates the value of sub national panel analysis in unpacking the complex interactions between inequality and development. Future research could extend the window beyond 2023, incorporate qualitative governance indicators, and test non-linear dynamics of inequality and growth. Such work will be critical for ensuring that India's development trajectory aligns with the ambition of SDG 10 and the broader 2030 Agenda.

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