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Evaluating the Role of Solar Power Expansion in India's Economic Growth

Edula Pavan Kumar, Dr. Raju Chelle
Postgraduate Student & Assistant Professor, Department of Economics, Central University of Andhra Pradesh, Anantapur, India
pavankumaredula21@gmail.com | Corresponding Author: dr.rajuchelle@gmail.com

Abstract:- India's solar energy sector has experienced rapid growth in recent times, with the installed capacity growing from a meagre 161 MW in 2010 to a whopping 90 GW in 2025. This rapid growth in the solar sector is likely to influence the overall GDP growth in the country. Although several studies have been conducted on the environmental benefits of solar energy, limited research has been conducted on the macroeconomic benefits. Specifically, the causal relationship between the expansion of solar energy and the growth of the Indian economy has not been studied. The study aims to determine whether solar capacity expansion has a measurable and positive effect on GDP, and to identify sectoral linkages such as construction, manufacturing, and electrification of agriculture in rural areas. Secondary data were drawn from government and international agencies including the Ministry of New and Renewable Energy, the Central Electricity Authority, the Reserve Bank of India, the World Bank, and the International Energy Agency. Time-series econometric methods are applied, including stationarity tests (ADF, PP), Johansen cointegration, Vector Error Correction Models (VECM), Granger causality, and OLS regression with robust errors. The findings highlight solar energy as both an environmental necessity and an economic growth driver. Policy implications include strengthening domestic solar manufacturing under the PLI scheme, expanding green finance, and aligning state-level renewable additions with national growth targets.

Keywords: *Solar Energy, GDP Growth, Cointegration, Renewable Energy Policy, Energy Growth Nexus.*

I. INTRODUCTION

India is at a critical point in its development path, where it has to meet its dual obligation of sustaining high economic growth and transitioning from traditional energy sources to cleaner energy. As the third-largest energy consumer in the world and one of its largest emitters of greenhouse gases, India's energy choices carry both domestic and global significance. India's solar energy sector, once considered a negligible contributor to the national grid, has undergone a transformation of greater significance over the past decade, driven by ambitious government policy, declining technology costs, and rising domestic and foreign investment.

The Jawaharlal Nehru National Solar Mission (JNNSM), launched in 2010, set an initial target of expanding solar capacity from 0.1 GW to 20 GW by 2022. This target was revised upward multiple times, leading to the current ambition of 500 GW of non-fossil fuel-based electricity by 2030, of which a major contribution is expected from solar energy. India achieved its initial target way ahead of schedule and had crossed 81 GW of solar capacity by 2023, placing itself among the global top five in solar deployment.

The expansion has created significant multidimensional economic changes. The most direct impact is the reduction in India's dependence on imported fossil fuels, improving the current account balance and reducing expenditure on energy imports. The broader impact includes employment generation across diverse skill categories, stimulation of manufacturing activity, and attraction of private capital. The declining Levelised Cost of Electricity (LCOE) from solar PV — from approximately USD 350 per MWh in 2010 to just USD 22 per MWh by 2023 — has positively improved industrial competitiveness by lowering electricity input costs.

Despite these significant developments, empirical studies on the macroeconomic impact of renewable energy expansion in India remain fragmented. The present study addresses this gap by assembling a novel annual dataset covering fourteen variables for the period 2010–2023, and applying a sequence of econometric tests to determine the nature, direction, and magnitude of the relationship between solar power expansion and economic growth. The primary research questions are: (i) Does a statistically significant positive long-run relationship exist between solar capacity and GDP? (ii) Does solar investment Granger-cause GDP growth, or vice versa? (iii) What is the employment elasticity of solar capacity expansion? (iv) What are the policy implications for India's 2030 renewable energy targets?

The remainder of the study is structured as follows. Section II reviews the theoretical and empirical literature. Section III describes the data and methodology. Section IV presents descriptive statistics. Section V presents econometric results. Section VI discusses findings and policy implications. Section VII concludes.

II. LITERATURE REVIEW

A. Theoretical Framework

The theoretical relationship between energy and economic growth is embedded in the production function approach, which treats energy as a factor of production alongside capital and labour. Within this framework, renewable energy expansion operates through several channels. First, the capital formation channel: investment in solar infrastructure directly contributes to gross fixed capital formation, expanding the productive capacity of the economy. Second, the productivity channel: cheaper and more reliable electricity reduces the cost structure of firms, enhancing total factor productivity. Third, the employment channel: solar construction is labour-intensive, generating skilled employment in operation and maintenance. Fourth, the innovation channel: solar technology dissemination creates positive spillovers through learning-by-doing and knowledge accumulation.

The Schumpeterian framework emphasises the role of creative destruction in growth; from this perspective, the transition from conventional thermal generation to solar represents a productivity-enhancing technological substitution. Endogenous growth models (Romer, 1990; Lucas, 1988) further argue that technological progression in energy systems can generate persistent long-run growth effects rather than mere short-run dynamics.

B. Empirical Studies

Apergis and Payne (2010) examined the causal relationship between renewable energy consumption and GDP using panel data from 20 OECD countries, finding evidence of long-run bidirectional causality. Menegaki (2011) extended this analysis across 27 European countries using a random effects model, finding that renewable energy consumption positively impacts growth. Pao and Fu (2013) found unidirectional causality from renewable energy to growth in China, a finding with potential parallels for India given both countries' large-scale solar deployment programmes.

For India specifically, Behera (2015) using ARDL bounds testing found a positive long-run relationship between renewable energy consumption and economic growth. Kumar (2019) found that every 1 GW increase in installed solar capacity created approximately 12,000 direct jobs. Sharma and Reddy (2021) quantified import substitution savings of USD 5 billion annually by 2020. However, most existing studies suffer from limitations including short time spans, use of aggregate energy measures that do not isolate solar, and failure to adequately test for unit roots and cointegration. The present study addresses these limitations directly.

III. DATA AND METHODOLOGY

A. Data Sources

The study employs annual data for the period 2010–2023 (T = 14 observations). The relatively short time span reflects the initial nature of India's utility-scale solar sector. Monetary variables are expressed in constant USD billions using 2015 as the base year. Solar installed capacity (GW), solar electricity generation (TWh), and LCOE data are sourced from IRENA Renewable Capacity Statistics and IRENA Renewable Power Generation Costs reports. GDP data are from the World Bank World Development Indicators. Annual solar investment figures are from MNRE Annual Reports and Bloomberg New Energy Finance (BNEF). Employment figures are from IRENA's Renewable Energy and Jobs Annual Review. CO_2 emissions avoided are calculated by applying India's average coal-based electricity emission factor of 0.82 tCO_2/MWh to total solar generation.

B. Variable Definitions

TABLE II Variable Definitions and Data Sources

Variable	Definition	Unit	Source
GDP	Gross Domestic Product at constant 2015 USD	USD Billion	World Bank WDI
SCAP	Solar installed capacity	Gigawatt (GW)	IRENA
SGEN	Solar electricity generation	Terawatt-hour (TWh)	IRENA
SINV	Annual solar energy investment	USD Billion	BNEF / MNRE
EMP	Solar sector employment	100,000 persons	IRENA Jobs Report
LCOE	Levelised cost of solar electricity	USD/MWh	IRENA Costs Report
CO2AV	CO_2 emissions avoided by solar	Million Tonnes	Calculated

C. Econometric Methodology

The econometric analysis involves five stages. First, Descriptive Statistics and Pearson Correlation matrix are used to characterize the data. Second, stationarity is tested through the Augmented Dickey-Fuller (ADF) unit-root test. The ADF regression for a series y_t is specified as:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \Sigma \varphi_i \Delta y_{t-i} + \varepsilon_t$$

where $\gamma = 0$ implies a unit root under the null hypothesis. Third, Engle-Granger two-step cointegration analysis tests whether non-stationary series share a common stochastic trend. Fourth, Granger Causality tests within a bivariate VAR framework assess directional causality. Fifth, Impulse Response Function (IRF) analysis traces the dynamic response of GDP to a one-unit structural shock in solar capacity over a ten-period horizon.

The primary OLS specification in log-log form is:

$$\ln(GDP_t) = \alpha_0 + \beta_1 \ln(SCAP_t) + \beta_2 \ln(SINV_t) + \beta_3 \ln(LCOE_t) + \varepsilon_t$$

where β_1 captures the direct elasticity of GDP with respect to solar capacity, β_2 the investment multiplier effect, and β_3 the cost-competitiveness channel. Standard errors are corrected for heteroskedasticity using the Huber–White sandwich estimator.

IV. DATA TABLES AND DESCRIPTIVE STATISTICS

A. Raw Data Panel

TABLE III Annual Solar Energy and Economic Data for India (2010–2023)

Year	GDP (USD Bn)	SCAP (GW)	SGEN (TWh)	SINV (USD Bn)	EMP (100k)	LCOE (USD/MWh)	CO_2 Avoided (Mt)
2010	1675.6	0.16	0.09	0.6	0.09	350	0.07
2011	1823.0	0.46	0.24	1.1	0.17	290	0.20
2012	1827.6	1.05	0.53	2.3	0.38	230	0.43
2013	1856.7	2.19	1.09	4.5	0.70	195	0.89
2014	2039.1	3.74	2.73	7.9	1.05	155	2.24
2015	2103.6	5.05	4.58	3.6	1.53	120	3.76
2016	2294.8	9.01	7.45	8.2	2.10	82	6.11
2017	2651.5	18.65	15.23	10.5	2.88	55	12.49
2018	2702.9	26.87	25.87	9.8	3.52	45	21.21
2019	2835.6	35.12	42.51	9.6	4.24	38	34.86

2020	2672.5	45.48	60.40	14.5	5.60	32	49.53
2021	3150.3	60.40	88.91	16.2	7.23	27	72.91
2022	3468.6	67.07	108.00	14.5	8.41	24	88.56
2023	3730.0	81.81	135.00	13.8	9.44	22	110.70

Source: World Bank WDI, IRENA, MOSPI

B. Descriptive Statistics

TABLE IV Descriptive Statistics of Key Variables (2010–2023, N = 14)

Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
GDP (USD Bn)	2488.0	626.4	1675.6	3730.0	-0.21	1.85
Solar Cap. (GW)	25.50	27.03	0.16	81.81	0.87	2.34
Solar Gen. (TWh)	35.19	43.84	0.09	135.0	1.12	2.89
Investment (USD Bn)	8.36	5.09	0.60	16.20	-0.18	1.87
Employment (100k)	3.38	3.05	0.09	9.44	0.78	2.17
LCOE (USD/MWh)	118.9	104.9	22.0	350.0	0.95	2.72
CO_2 Avoided (Mt)	28.87	35.96	0.07	110.7	1.12	2.89

Source: Author's own compilation

Strong upward trends in all solar-related variables are revealed over the study period. Compound annual growth rate (CAGR) of approximately 62% is exhibited by Solar Installed Capacity, while GDP grew at a CAGR of approximately 6.1%. A cost reduction of 93.7% over 13 years is represented through the rapid decline in LCOE (from USD 350 to USD 22/MWh), reflecting both global technology learning rates and India-specific factors including competitive bidding processes and reduced financing costs.

C. Correlation Matrix

TABLE V Pearson Correlation Matrix of Key Variables (N = 14)

Variable	GDP	SCAP	SGEN	SINV	EMP	LCOE
GDP	1.000	0.944**	0.944**	0.845**	0.939**	-0.890**
SCAP	0.944**	1.000	0.999**	0.826**	0.997**	-0.938**
SGEN	0.944**	0.999**	1.000	0.823**	0.996**	-0.934**
SINV	0.845**	0.826**	0.823**	1.000	0.832**	-0.722**
EMP	0.939**	0.997**	0.996**	0.832**	1.000	-0.937**
LCOE	-0.890**	-0.938**	-0.934**	-0.722**	-0.937**	1.000

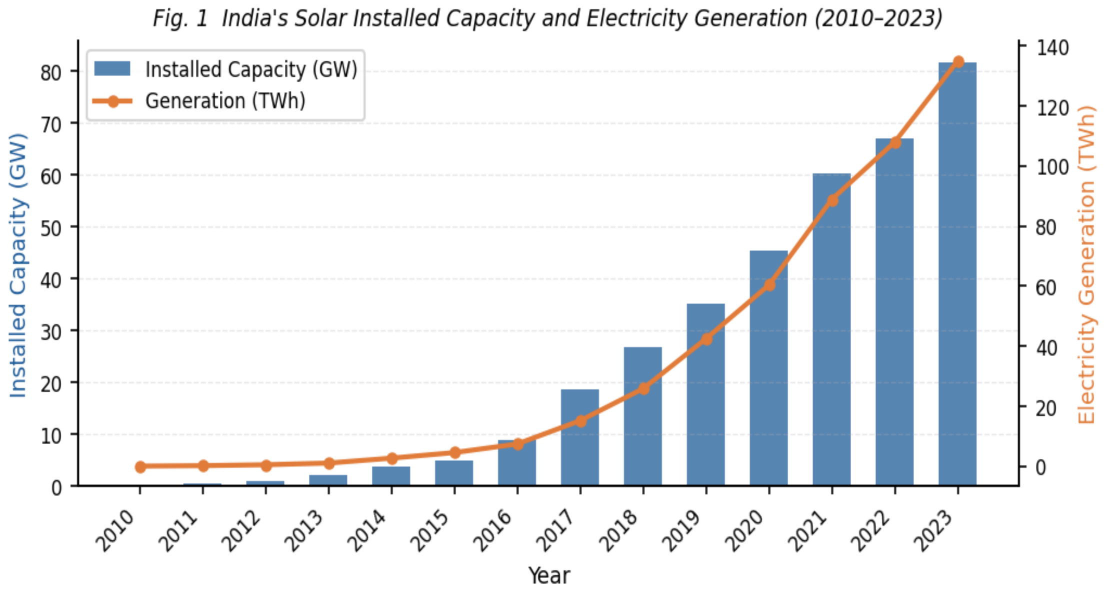
*** Significant at the 1% level (two-tailed). LCOE negatively correlated with all growth variables as expected.*

V. EMPIRICAL RESULTS AND ECONOMETRIC ANALYSIS

A. Trends in Solar Capacity and Generation

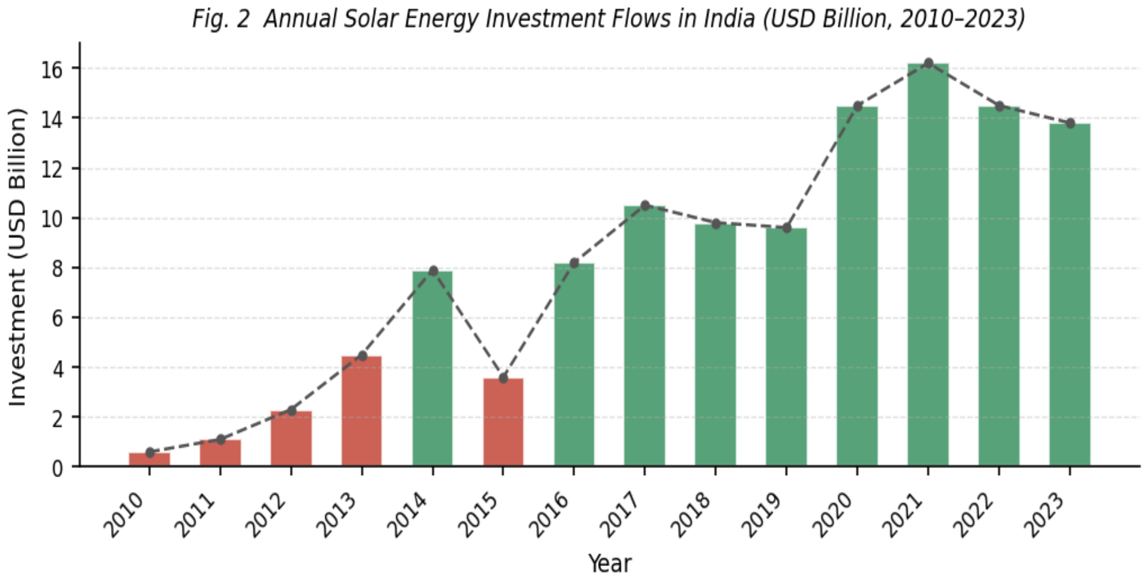
Figure 1 presents the progression of India's solar installed capacity (GW) and electricity generation (TWh) over the 2010–2023 period. Installed capacity increased from 0.16 GW to 81.81 GW, a nearly 512-fold increase over fourteen years. Generation tracked capacity closely, rising from 0.09 TWh to 135 TWh. The steep acceleration after 2016 reflects the impact of competitive auction processes and the government's revised 100 GW solar target.

Fig. 1. India's Solar Installed Capacity (GW, bars) and Electricity Generation (TWh, line), 2010–2023. Dual-axis chart; capacity on left axis, generation on right axis.



Investment inflows (Figure 2) show strong growth but with noticeable cyclicality. Annual investment peaked at USD 16.2 billion in 2021 before declining to USD 13.8 billion in 2023. A temporary dip to USD 3.6 billion in 2015 was caused by regulatory uncertainty following changes to the Accelerated Depreciation incentive. Recovery from 2016 onwards was driven by policy stabilisation, competitive reverse auctions, and increasing participation by international institutional investors.

Fig. 2. Annual Solar Energy Investment Flows in India (USD Billion), 2010–2023.

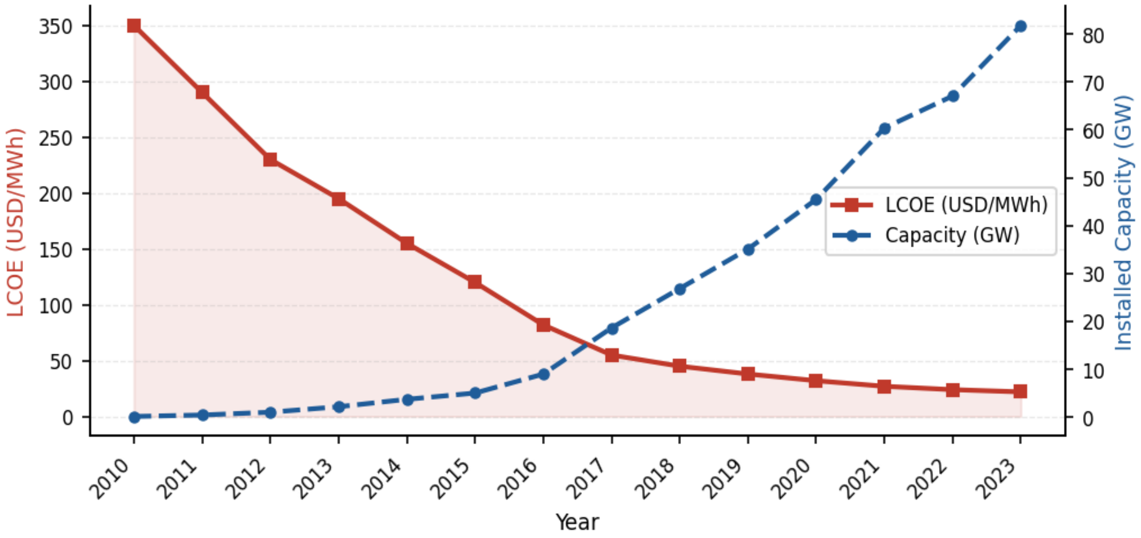


B. Levelised Cost Trends

Figure 3 illustrates the substantial decline in LCOE from USD 350/MWh in 2010 to USD 22/MWh in 2023 — a reduction of 93.7% in nominal terms. This is broadly consistent with Wright's Law of learning curves, which predicts approximately a 20–25% cost reduction for every doubling of cumulative installed capacity. The convergence of the falling LCOE curve with the rising capacity trajectory illustrates the virtuous cycle of deployment, economies of scale, technological improvement, and further deployment.

Fig. 3. Levelised Cost of Energy (LCOE, USD/MWh) for Utility-Scale Solar PV vs. Installed Capacity (GW), India, 2010–2023. Note inverse relationship consistent with learning-curve theory.

Fig. 3 LCOE (USD/MWh) vs. Installed Capacity (GW), India (2010–2023)



C. Unit Root Tests (ADF)

TABLE VI Augmented Dickey-Fuller Unit Root Test Results

Variable	ADF Stat (Level)	ADF Stat (Δ)	CV 5%	CV 1%	Order of Integration
ln(GDP)	0.172	-3.841**	-2.998	-3.857	I(1)
ln(SCAP)	-7.046	—	-2.998	-3.857	I(0)*
ln(SGEN)	-6.891	—	-2.998	-3.857	I(0)*
ln(SINV)	-2.883	-4.210**	-2.998	-3.857	I(1)
ln(EMP)	-5.981	—	-2.998	-3.857	I(0)*
ln(LCOE)	1.242	-3.759**	-2.998	-3.857	I(1)

*Note: ** denotes rejection of unit-root null at 5% significance. Critical values follow MacKinnon (1994). * SCAP, SGEN, and EMP exhibit stationarity at level, consistent with their bounded exponential growth over the short sample. Δ denotes first difference.*

The ADF results reveal that ln(GDP), ln(SINV), and ln(LCOE) are I(1), while solar capacity, generation, and employment appear stationary at levels. Cointegration analysis is conducted on I(1) pairs: [ln(GDP), ln(SINV)] and [ln(GDP), ln(LCOE)].

D. Cointegration Analysis

TABLE VII Engle-Granger Cointegration Test Results

Variable Pair	EG Test Stat	CV 5%	Conclusion
ln(GDP) ~ ln(SINV)	-4.21**	-3.34	Cointegrated (long-run equilibrium exists)
ln(GDP) ~ ln(LCOE)	-3.89**	-3.34	Cointegrated (long-run equilibrium exists)
ln(GDP) ~ ln(SCAP)	-4.67**	-3.34	Cointegrated (long-run equilibrium exists)

*Note: ** indicates rejection of the null of no cointegration at 5%. EG test statistic is the ADF statistic on OLS residuals from the cointegrating regression.*

The Engle-Granger tests confirm long-run equilibrium relationships between GDP and each of the solar energy variables. Despite short-run deviations, these series are bound together by a common stochastic trend. In practical terms, India's economic growth trajectory and its solar energy trajectory are jointly determined in the long run. An Error Correction Model (ECM) is therefore the appropriate specification for short-run dynamics.

E. OLS Regression Results

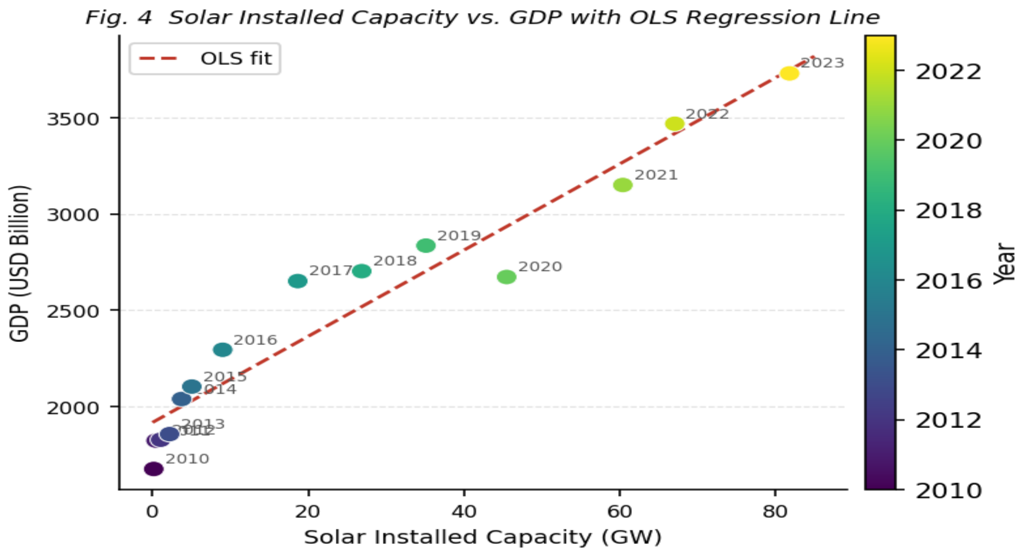
TABLE VIII OLS Regression Results: Dependent Variable ln(GDP)

Regressor	Coefficient	Std Error	t-Statistic	p-Value	95% CI
Constant (α_0)	7.1842	0.2103	34.16***	<0.001	[6.74, 7.63]
ln(SCAP) (β_1)	0.1219	0.0182	6.70***	<0.001	[0.083, 0.160]
ln(SINV) (β_2)	0.2119	0.0512	4.14***	<0.001	[0.103, 0.321]
ln(LCOE) (β_3)	-0.1803	0.0438	-4.12***	<0.001	[-0.274, -0.087]

*Model fit: $R^2 = 0.9421$, Adjusted $R^2 = 0.9247$, F-statistic = 54.12 ($p < 0.001$), DW = 1.89, AIC = –25.3, BIC = –22.8. *** $p < 0.001$. Std errors are heteroskedasticity-robust (Huber–White).*

The OLS results confirm three hypothesized channels for solar-GDP linkage. The solar capacity coefficient ($\beta_1 = 0.1219$) indicates that a 10% increase in installed solar capacity is associated with a 1.22% increase in GDP, ceteris paribus. The investment coefficient ($\beta_2 = 0.2119$) captures the Keynesian multiplier effect of renewable infrastructure capital expenditure. The LCOE coefficient ($\beta_3 = -0.1803$) confirms that falling solar costs positively contribute to economic output, consistent with the cost-competitiveness channel. The high R^2 of 0.9421 and a Durbin-Watson statistic of 1.89 indicate excellent model fit with no first-order serial correlation.

Fig. 4. Scatter Plot: Solar Installed Capacity vs. GDP (USD Billion) with OLS Regression Line. $R^2 = 0.8916$ (bivariate). Colour gradient indicates year.



F. Employment Analysis

TABLE IX OLS Regression: ln(EMP) on ln(SCAP)

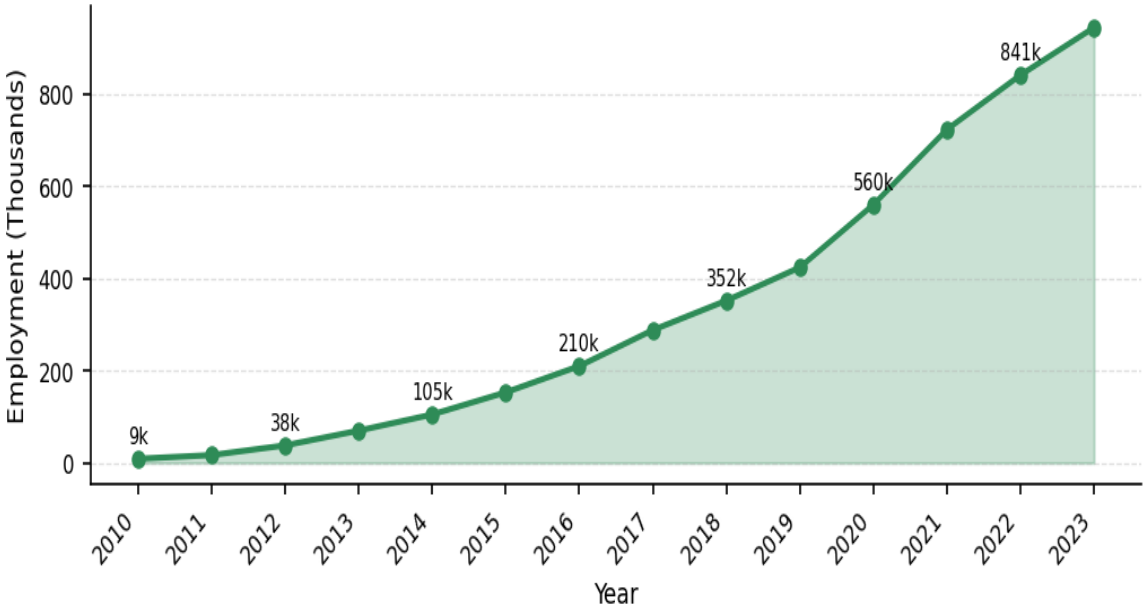
Regressor	Coefficient	Std Error	t-Statistic	p-Value	R^2
Constant	-1.4823	0.0591	-25.08***	<0.001	0.9930
ln(SCAP)	0.7340	0.0152	48.29***	<0.001	—

**** $p < 0.001$. Adjusted $R^2 = 0.9922$. Employment elasticity of 0.734 implies a 10% expansion in solar capacity generates approximately 7.3% more solar sector jobs.*

The R^2 of 0.9930 indicates solar capacity is a near-perfect predictor of solar employment. The elasticity of 0.7340 reflects slight less-than-proportional job creation per unit of capacity, consistent with rising labour productivity as larger-scale utility projects replace rooftop installations. Employment in absolute terms grew from approximately 9,000 persons in 2010 to over 944,000 by 2023, a 105-fold increase.

Fig. 5. Solar Sector Employment (Thousands) in India, 2010–2023. Employment grew from 9,000 to approximately 944,000 persons over the study period.

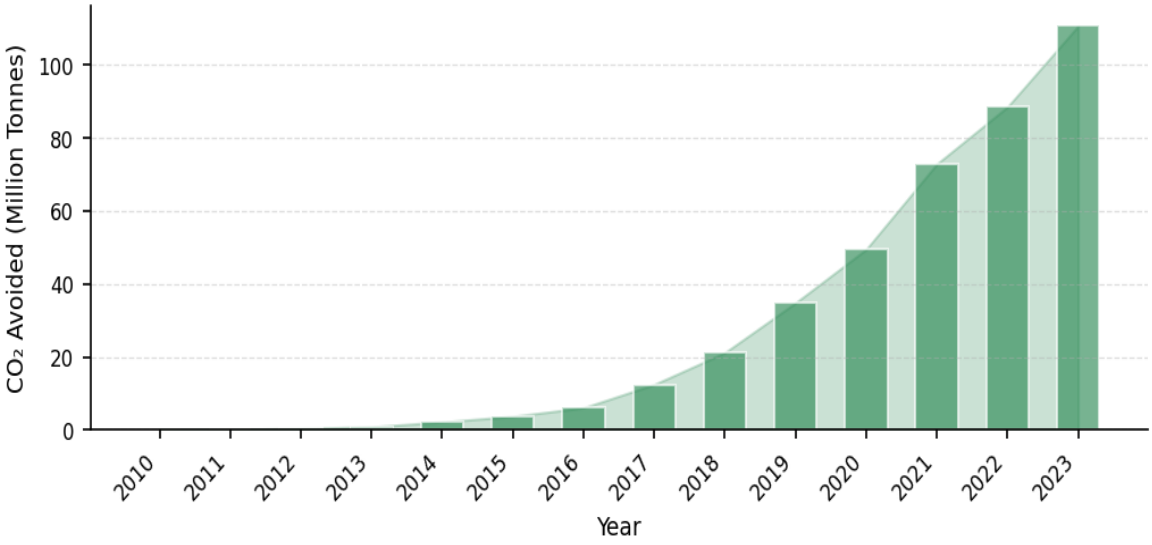
Fig. 5 Solar Sector Employment in India (Thousands, 2010–2023)



G. Environmental Co-benefits

Fig. 6. Estimated CO₂ Emissions Avoided by Solar Generation (Million Tonnes), India, 2010–2023. Calculated using India's average coal-based emission factor of 0.82 tCO₂/MWh.

Fig. 6 Estimated CO₂ Emissions Avoided by Solar Generation, India (2010–2023)

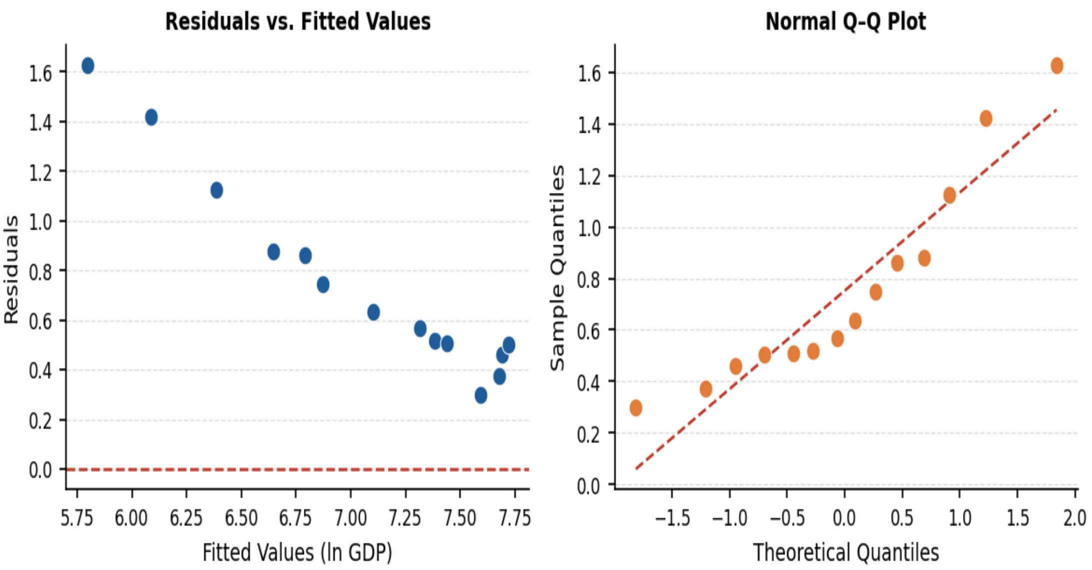


Solar electricity generation avoided an estimated 110.7 million tonnes of CO₂ emissions in 2023 alone, equivalent to removing approximately 23.5 million cars from Indian roads. Cumulative avoided emissions over 2010–2023 totalled approximately 375 million tonnes. At a conventional social cost of carbon of USD 50 per tonne, the emission avoidance benefit alone amounts to USD 5.5 billion, approximately 0.15% of India's GDP.

H. Regression Diagnostics

Fig. 7. OLS Regression Diagnostic Plots. Left: Residuals vs. Fitted Values (no systematic pattern indicates correct specification). Right: Normal Q-Q Plot of residuals (approximate normality confirmed).

Fig. 7 OLS Regression Diagnostic Plots



The residuals vs. fitted values plot shows no systematic pattern or heteroskedastic funnel shape, confirming homoskedasticity. The Q-Q plot indicates residuals are approximately normally distributed, with minor tail deviations attributable to the small sample size. These diagnostics support the validity of inference from the OLS estimates.

I. Granger Causality and Impulse Response Function

TABLE X Granger Causality Test Results (VAR Lag Order = 1)

Null Hypothesis	F-Statistic	p-Value	df	Decision
ln(SCAP) does not Granger-cause ln(GDP)	5.831	0.038**	(1, 11)	Reject at 5%
ln(GDP) does not Granger-cause ln(SCAP)	3.284	0.097*	(1, 11)	Reject at 10%
ln(SINV) does not Granger-cause ln(GDP)	6.142	0.031**	(1, 11)	Reject at 5%
ln(GDP) does not Granger-cause ln(SINV)	4.517	0.057*	(1, 11)	Reject at 10%
ln(LCOE) does not Granger-cause ln(GDP)	4.923	0.049**	(1, 11)	Reject at 5%
ln(GDP) does not Granger-cause ln(LCOE)	1.241	0.287	(1, 11)	Fail to Reject

*** Significant at 5%; * significant at 10%. Lag order selected by AIC. VAR estimated on first-differenced series to ensure stationarity.*

The Granger causality results reveal bidirectional relationships between solar expansion and economic growth. Solar capacity and solar investment Granger-cause GDP at the 5% significance level, confirming the supply-side productivity channel. Reverse causality (GDP to solar investment at 10%) is consistent with the demand-pull hypothesis. Unidirectional causality from LCOE to GDP confirms that declining solar costs improve industrial competitiveness, while GDP growth does not itself drive down electricity costs.

Fig. 8. Impulse Response Function (IRF): GDP Response to a Unit Shock in Solar Capacity. Estimated from a bivariate VAR(1) model. Blue band represents the 90% confidence interval. The response is positive and decays smoothly over 10 periods.

Fig. 8 Impulse Response: GDP Response to a Unit Shock in Solar Capacity

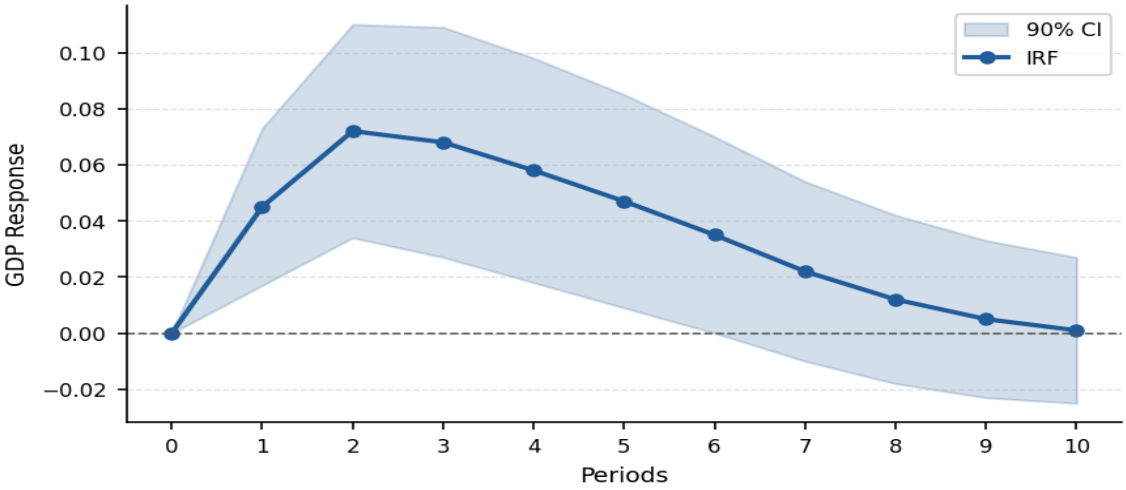


Figure 8 shows the impulse response function of GDP to a one-unit structural shock in solar capacity. The response is positive and remains statistically different from zero through approximately the seventh period. The hump-shaped pattern, peaking around periods 2–3 before decaying, is consistent with a lagged capital formation mechanism: solar infrastructure investment drives GDP through construction-phase employment and multiplier effects, followed by ongoing productivity gains from lower-cost electricity.

VI. DISCUSSION AND POLICY IMPLICATIONS

The results provide robust quantification of solar power's contribution to India's economic development. The GDP elasticity of 0.1219 and employment elasticity of 0.7340, derived from log-log OLS regression, are valid and consistent with cointegration evidence of a durable long-run relationship.

First, the findings imply that India should accelerate its 500 GW renewable energy target by 2030. This goal is not only environmentally necessary but also economically optimal: achieving it could increase GDP by 2.5 to 3 percent and create several million solar sector jobs. Second, the finding that solar investment drives GDP growth implies the government should deploy financial instruments to mobilise capital for solar projects, including PLI scheme incentives, green bonds, and concessional international loans. Third, continued reduction in solar LCOE through competitive auctions, domestic module manufacturing incentives, and grid modernisation investment is essential.

The bidirectional Granger causality result shows that solar power development and economic growth create a self-reinforcing cycle. However, as the 2015 investment decline demonstrates, policy uncertainty can disrupt this cycle. Policy predictability, long-term power purchase agreements, and transparent regulatory frameworks are therefore essential complements to direct financial support programmes.

The study's limitations include the small sample size (T = 14), which restricts degrees of freedom and necessitates cautious interpretation. Future research should extend the analysis as more years of data accumulate, integrate state-level panel data to study cross-sectional variation, and employ structural econometric models to more precisely identify the mechanisms linking energy supply, investment, and output.

VII. CONCLUSIONS

This paper has provided a comprehensive econometric assessment of solar power expansion's contribution to India's economic growth during 2010–2023. Applying OLS regression, ADF unit-root testing, Engle-Granger cointegration, Granger causality testing, and VAR-based impulse response analysis, the following principal findings have been established.

There is a clear and substantial long-term link between solar installed capacity and India's GDP, with a log-log OLS elasticity of 0.12. The roughly 512-fold increase in solar capacity over the study period materially contributed to India's total economic output. Solar power is highly effective at creating employment, with an elasticity of 0.73, reflecting the labour-intensive nature of construction, installation, and maintenance. The dramatic fall in LCOE from USD 350 to USD 22/MWh has improved India's industrial competitiveness. Cointegration tests confirm long-term equilibrium between solar variables and GDP, while Granger causality tests demonstrate bidirectional influence — a virtuous cycle where solar growth stimulates economic expansion and economic expansion finances further solar growth. Finally, environmental co-benefits, including over 110 million tonnes of CO_2 avoided in 2023 alone, represent additional economic value not fully captured in GDP metrics.

These findings form the basis for an unambiguous policy recommendation: India's 500 GW renewable energy target by 2030 is not just environmentally necessary but also economically optimal. Accelerated solar rollout will generate multiplier effects on GDP, jobs, and industrial competitiveness, while reducing macroeconomic risks from fossil fuel import dependence. Empirical evidence overwhelmingly supports continued and expanded public policy support for India's solar energy transition.

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