

# Solar Deployment, State Economic Output, and Sectoral Employment in India: Evidence from State-Level Panel Data

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## Abstract

*This study examines how the deployment of grid-connected solar photovoltaic capacity relates to state economic output and employment across India. Drawing on an unbalanced panel of 28 states from 2012 to 2023, it estimates the within-state relationship between installed solar capacity and real Net State Domestic Product (NSDP) using state fixed-effects models. Employment outcomes are accounted for separately, using 2022-23 state-level indicators from the Periodic Labour Force Survey that distinguish aggregate labour-force participation from manufacturing employment. The results point to a positive within-state relationship between solar capacity and real NSDP. Moreover, the estimate stays positive and statistically significant when capacity is lagged by one year. Solar capacity shows no significant association with aggregate labour-force participation, whereas the association with manufacturing employment is positive. Taken together, these findings suggest that the economic gains from solar deployment may register more clearly in state output and in sector-specific employment than in aggregate labour-market participation. They also underline the value of accounting for sectoral heterogeneity when weighing the socioeconomic effects of India's energy transition.*

**Keywords:** solar energy; economic growth; employment; Indian states; panel fixed effects; energy transition

**JEL:** Q42, Q48, O13, R11

## 1. Introduction

India's solar build-out over the past decade is, by any headline measure, a success. Grid-connected solar capacity rose from close to nothing in 2010 to 81,814 megawatts by the end of the 2023-24 financial year, which is fifty-seven per cent of all grid-interactive renewable capacity in the country (Ministry of Statistics and Programme Implementation, 2025). Auction tariffs fell from above seventeen rupees per kilowatt-hour in 2010 to under two and a half by the late 2010s, solar overtook wind inside the non-hydro renewable basket, and the 100 GW target set in 2015 was met, two years late, in early 2024. Recent syntheses confirm the trajectory, placing solar as the fastest-growing segment of the renewable build-out and reporting a strong aggregate association between renewable capacity and state output (Kumbhar, Satpute and Patil, 2026). Read at the national level, the transition looks like a policy that worked.

Read at the level of states, the same numbers tell a more uncomfortable story. Deployment has been concentrated in a small western and southern cluster. Rajasthan and Gujarat alone account for close to forty-five per cent of installed capacity, the top five states hold roughly three-quarters of it, and the concentration has been widening rather than narrowing over time (MoSPI, 2025). Most of India, in other words, has barely deployed. The national headline describes what a handful of states have done, not what the country as a whole has done, and that gap is where this paper begins.

The policy narrative that has accompanied the build-out assumes a particular chain of consequences: a new solar park brings construction, operations and maintenance work, ancillary manufacturing, and cheaper power for industry, and eventually higher output and more jobs in the state that hosts it. The argument is intuitive, and governments have made it routinely when setting targets. Whether it survives contact with the data is a separate question, because solar is

capital-intensive and increasingly automated, and can raise industrial output without moving aggregate employment. The way to find out is to ask directly: when a state adds solar capacity, holding constant everything else about that state, what happens to its income and to its employment?

Using an unbalanced panel of twenty-eight states from 2012 to 2023, I estimate the within-state relationship between installed grid-connected solar capacity and Net State Domestic Product with a state fixed-effects model, and I read the employment side through a 2022-23 cross-section of aggregate and manufacturing labour indicators from the Periodic Labour Force Survey. The results split in a way that is, I will argue, the substantive finding rather than a complication. On the output side the relationship is positive and robust: a one per cent rise in a state's installed solar capacity is associated with roughly a 0.068 per cent rise in its real NSDP once every time-invariant feature of the state has been absorbed, and the estimate barely moves when capacity is lagged by a year to address reverse causality. On the employment side the relationship depends entirely on where one looks. Aggregate labour force participation shows no measurable response. The manufacturing employment rate, which is the sectoral channel through which the international literature predicts solar's labour footprint should run, responds positively, with an elasticity of 0.129. In short, the build-out has lifted output and manufacturing employment while leaving the aggregate labour market unmoved.

The contribution is deliberately specific. I do not claim to settle whether renewables drive growth, a question still argued both internationally and in the Indian context. The narrower claim is that, for the Indian case and over the window in which state-level solar data have become reliable, this three-part pattern is what the renewable-growth and renewable-jobs literatures would jointly predict, and that documenting it within a single design changes how the transition should be justified. The rest of the paper proceeds as follows. Section 2 places the study in the literature on energy and growth, on solar and output, and on renewables and employment. Section 3 sets out the policy and deployment context that makes the state the right

unit of analysis. Sections 4 and 5 describe the data and the empirical strategy. Section 6 reports the results, Section 7 discusses the output-employment split, and Section 8 concludes.

## 2. Related literature

### 2.1 *Energy in the growth process*

Growth theory took a long time to take energy seriously. The neoclassical model that Solow (1956) put into circulation treats output as a combination of capital, labour, and a residual technological term, with energy entering, when it enters at all, as one input among many. The endogenous-growth models of the late 1980s and 1990s reopened the door: once knowledge spillovers, research and development, and capital reallocation are placed at the centre of long-run growth, the energy system becomes, in principle, a channel through which structural change can raise productivity (Acemoglu et al., 2012). Court, Jouvet and Lantz (2018) make the argument explicit, building an endogenous-growth model in which investment in renewable energy is optimised and the resulting transition raises total factor productivity through lower energy costs and capital reallocation. The corollary that matters for an Indian study is that the size of this output response depends on the receiving economy's capacity to put cheaper electricity to productive use, so the effect is conditional on absorptive capacity rather than uniform (Stern, 2011). That is the analytical reason to work within a large and internally varied country rather than across countries or at its national aggregate: if absorptive capacity varies across states, a national estimate averages over the variation of interest and a pooled cross-state estimate confounds the solar effect with the industrial structure that conditions it.

### 2.2 *Solar deployment and output*

Cross-country work that isolates solar, rather than treating renewables as a bundle, is recent but broadly positive. Liao et al. (2025) find that solar carries the largest growth effect among renewable sources and that pooling the sources obscures it; Güney (2022) links solar to development indicators beyond GDP across thirty-five countries; and Xu, Geng and Javed (2025) find the effect concentrated

at higher income levels, a threshold pattern rather than a uniform one, consistent with Obani, Izu-Obani and Akroh's (2024) insignificant estimate at low adoption. The methodological lesson that recurs is that isolating solar recovers cleaner estimates than pooling it with hydro and wind. Indian evidence confirms the direction but stops short of this specific question: Bhavsar, Bendigiri and Samanta (2025) report a robust renewable-growth relationship without separating solar from the composite, and Khan et al. (2025) find weaker, sometimes negative, effects once the costs of grid integration and distribution company (DISCOM) finance are entered explicitly.

Two Indian panels published since bear directly on the output question while leaving the present gap open. Poojari and Rathod (2026), using state fixed effects over 2005 to 2023, report that a ten per cent rise in installed renewable capacity is associated with about a 1.42 per cent rise in state product, and that a state's human capital conditions how far it converts that capacity into output. Gupta and Guha (2024) go further on method, using system generalised method of moments and a vector error-correction model, and find that solar capacity in particular raises state output; their dynamic design reads closer to a causal effect than the estimates recovered here, though it too stays at the level of output alone.

### ***2.3 Solar deployment and employment***

The employment literature is more contested, and it turns on one distinction. Gross employment counts the jobs added to the renewable sector; net employment subtracts those displaced in coal, in thermal generation, and in whichever activity the diverted capital would otherwise have funded. Meyer and Sommer (2014) draw the distinction, and Stavropoulos and Burger (2020) show its bite: in their meta-regression, studies that count induced effects are about half as likely to report a positive net effect as studies reporting only gross jobs. The size of the reported effect is, in large part, a function of what is netted out.

Where solar's labour footprint does register, it sits in construction and manufacturing supply chains rather than in operations and maintenance, whose steady-state requirement is small (Hanna,

Heptonstall and Gross, 2024; Lehr, Lutz and Edler, 2012). This has a mechanical implication for a state panel: with labour intensity concentrated in a short construction window and a thin steady-state footprint, aggregate employment effects track the rate of fresh capacity addition rather than the stock of installed capacity, and in a labour market of tens of millions such a footprint is unlikely to surface in an aggregate participation rate. Studies using very different methods reach the same aggregate conclusion while locating the effect sectorally (Böhringer, Keller and van der Werf, 2013; Pestel, 2019; Fabra et al., 2024), and Rahman, Rahman and Akter (2024) find no aggregate employment response to renewable expansion across South Asia. The prior is straightforward: the signal, if any, belongs in a sectoral series rather than an aggregate one, which is what the empirical design tests.

Recent Indian evidence sharpens the same point at the level this paper works with. Shharma et al. (2025), estimating a fixed-effects panel across twenty-eight states, find that solar is more job-intensive than wind yet that renewable investment on its own produces no significant aggregate employment gain unless it is paired with workforce development and local-content requirements. That a state-level Indian panel returns an aggregate null while still locating solar's labour advantage in its more employment-intensive segments is close to the split this paper documents. It reinforces the case for reading employment sectorally rather than in aggregate.

### ***2.4 Synthesis and research gap***

Two threads run through these literatures. The output evidence is strongest where solar is isolated from the renewable composite, and the employment evidence clearest where jobs are read by sector rather than in aggregate, so disaggregation on both sides is what lets the evidence speak. And the variation in effects across economies is not noise around a single elasticity but the finding itself, since institutional and industrial capacity, not physical solar resource, is what conditions the response. The gap follows directly. Existing Indian evidence appears to offer only limited state-level analysis that simultaneously

isolates solar deployment and examines both economic output and sector-specific employment. The Indian panels that study output either pool the renewable types (Bhavsar, Bendigiri and Samanta, 2025; Poojari and Rathod, 2026) or, where they isolate solar, do so for output alone (Gupta and Guha, 2024; Gururaghavendra and Prasad, 2024); Shrimali, Agarwal and Donovan (2020) study deployment's drivers rather than its effects; the state-level work that does reach employment reads it through job counts on a pooled renewable measure rather than through a sectoral rate (Sharma et al., 2025); and the cross-country solar studies isolate solar but stop at the national level (Li, 2024; Xu, Geng and Javed, 2025; Liao et al., 2025). This paper occupies the space they leave.

### 3. Policy and deployment context

India's solar transition is, in the first instance, a policy product, but the policy is made at two levels, and the division between them is what makes the states the right place to look. Electricity sits on the Concurrent List of the Constitution, and a settled division of labour has emerged in practice: the central government sets capacity targets, funds the national mission, runs the Solar Energy Corporation of India as a central procurement agency, and negotiates international finance, while the states own the DISCOMs that sign the power-

purchase agreements, set retail tariffs, enforce or fail to enforce the renewable purchase obligations notified by their regulators, and control the land and clearances that decide whether a project is built at all (Busby and Shidore, 2020; Shrimali, Agarwal and Donovan, 2020). The same central subsidy can therefore produce very different outcomes in two states, because the tariff structure, the financial health of the DISCOM, the transmission situation, and the political priority attached to renewables are all state-level variables (Khan et al., 2025).

The visible consequence is a concentration that has deepened as deployment has scaled. The five leading states hold roughly 76 per cent of national grid-connected capacity at the end of the period studied here, up from about 70 per cent a decade earlier (Figure 1). The leaders combine high irradiance with available land, financially healthier DISCOMs, and continuity of state-level policy, while the laggards are short of one or more of these, and several run no dedicated state solar policy at all. The institutional account of why particular states lead is not the subject of this paper, which takes the deployment pattern as given and asks what it has meant for state economies. What matters here is that the variation is real, it is large, and it lives at the level of states.

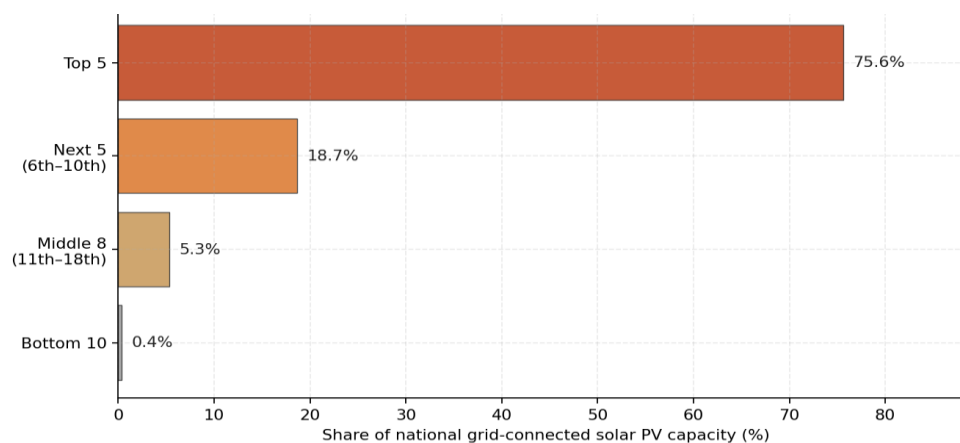


**Figure 1.** Concentration of installed grid-connected solar PV capacity across Indian states, 2024. Share of national capacity held by the top five, next five, middle eight, and bottom ten states.

That fact dictates the empirical design. A pooled estimator comparing states to one another would be dominated by the small cluster of heavy deployers, and would confound the effect of solar with the

industrial base, infrastructure, and institutions that drive both deployment and income in those states. A national time series would go to the opposite extreme, erasing the inter-state variation. The state-

year panel resolves both problems by letting each state serve as its own control over time, so that the slow-moving state characteristics a cross-state comparison would mistake for a solar effect are held constant, and the within-state question remains: whether a state's income and employment move with its own solar capacity. Section 4 describes the data assembled to answer it, and Section 5 the estimator.

## 4. Data

The analysis draws on three official sources, each reporting at the state-year level, and covers twenty-eight Indian states. Telangana and the union territories are excluded because their state-level series are not consistently reported across the study window. Table 1 lists the variables, their definitions, and their sources; Table 2 reports descriptive statistics.

### 4.1 Variables

The regressor of interest is grid-connected solar photovoltaic installed capacity, measured in megawatts at the end of each financial year, compiled from the Energy Statistics India reports of the Ministry of Statistics and Programme Implementation (MoSPI, 2025). Two features of the series should be kept in mind. It records grid-

connected capacity only, so off-grid and behind-the-meter installations lie outside it. And it measures installed rather than generated capacity, so the coefficient is an elasticity with respect to capacity in place, not electricity produced.

The output variable is Net State Domestic Product at constant 2011-12 prices, in rupees lakh, taken from the state NSDP tables of MoSPI and cross-checked against the Reserve Bank of India's Handbook of Statistics on Indian States. Constant prices strip out the state-specific inflation a nominal series would carry, so the estimate reads as a real output response. The series is published a year in arrears, which sets the panel's final year.

Employment is measured from the Periodic Labour Force Survey (NSO) in two ways. The aggregate indicator is the Labour Force Participation Rate for the working-age population. The sectoral indicator is a manufacturing employment rate, constructed as the working-age worker-population ratio multiplied by the share of workers whose principal industry is manufacturing, which isolates the sector to which the literature in Section 2.3 points. The PLFS series begins only in 2017-18 and is too short to anchor a fixed-effects panel, so employment is tested in the cross-section rather than the panel.

**Table 1.** Variable definitions and sources.

| Variable                          | Definition                                                                                               | Source                                                               |
|-----------------------------------|----------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------|
| Installed solar capacity          | Grid-connected solar PV capacity in place at the end of the financial year (MW).                         | Energy Statistics India, MoSPI (2025)                                |
| Net State Domestic Product (NSDP) | Real state output at constant 2011-12 prices (rupees lakh).                                              | MoSPI state NSDP tables; RBI Handbook of Statistics on Indian States |
| Labour Force Participation Rate   | Share of the working-age (15+) population in the labour force.                                           | Periodic Labour Force Survey, NSO                                    |
| Manufacturing employment rate     | Working-age worker-population ratio $\times$ share of workers whose principal industry is manufacturing. | Periodic Labour Force Survey, NSO                                    |

### 4.2 Sample and panel construction

The panel runs from 2012 to 2023 across the twenty-eight states and is unbalanced, with 285 state-year observations: cells in which installed capacity is exactly zero drop out of the logarithmic specification, and the smallest north-eastern states

contribute fewer years than the rest. The employment cross-section uses 2022-23, the most recent year in which output, solar capacity, and the labour indicators are jointly observed for all twenty-eight states. Figure 2 shows the resulting coverage.

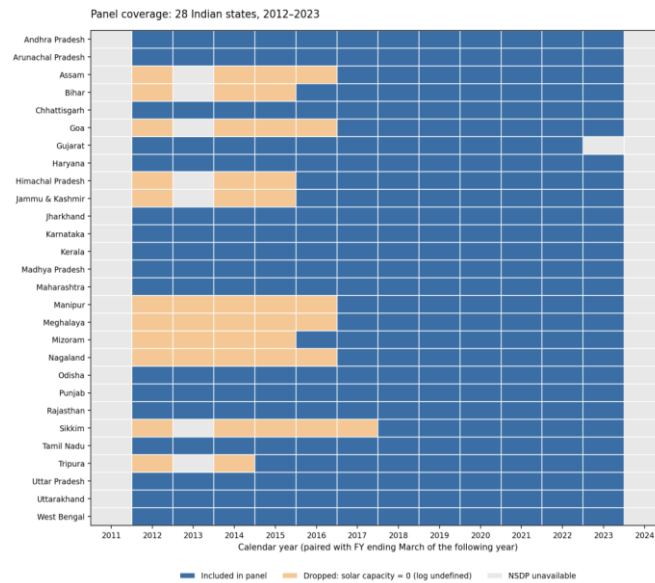


**Figure 2.** Panel coverage, 28 Indian states, 2012–2023. Blue cells enter the fixed-effects estimation; amber cells drop out because installed capacity is zero (log undefined); grey cells are years for which constant-price NSDP is not yet published.

**Table 2.** Descriptive statistics.

| Variable                                | N   | Mean       | SD         | Min       | Max         |
|-----------------------------------------|-----|------------|------------|-----------|-------------|
| Installed solar capacity (MW)           | 285 | 844.79     | 1,923.05   | 0.01      | 17,055.70   |
| NSDP (constant 2011-12 prices, Rs lakh) | 285 | 42,829,160 | 41,517,362 | 1,039,877 | 210,759,726 |
| Labour Force Participation Rate (%)     | 28  | 64.33      | 7.41       | 50.90     | 81.30       |
| Manufacturing employment rate (%)       | 28  | 5.58       | 2.94       | 1.42      | 14.62       |

*Solar capacity and NSDP are summarised over the 2012-2023 panel (285 state-year observations); the labour indicators over the 2022-23 cross-section (28 states). NSDP is in rupees lakh at constant 2011-12 prices.*

## 5. Empirical strategy

### 5.1 The identification problem

Across the twenty-eight states, output and solar capacity move together very closely: the two series correlate at about 0.93, and a simple cross-sectional regression of log NSDP on log solar capacity for 2022-23 returns an elasticity of roughly 0.572. Neither figure should be read as an effect. A correlation that near one is a warning rather than a confirmation: as Section 3 argued, the states that have deployed most differ from the rest in ways that raise output on their own, so a comparison across states loads those differences onto the solar coefficient. The cross-sectional elasticity is best treated as a confounded benchmark, useful mainly

as the number against which the within-state estimate is read. Separating the effect of solar from the state characteristics bundled into it is what the panel is for.

### 5.2 The within-state model

The primary specification is a within-group, state fixed-effects panel:

$$\log(NSDP_{it}) = \alpha_i + \beta \log(Solar_{it}) + \varepsilon_{it}$$

where  $i$  indexes states,  $t$  financial years,  $Solar$  is installed grid-connected capacity, and  $\alpha$  is a state-specific intercept. The coefficient  $\beta$  is the elasticity of real NSDP with respect to installed capacity, the average percentage change in a state's output associated with a one per cent rise in its own capacity. The state intercept absorbs everything

about a state that does not move over the study window, its solar resource, its industrial history, its stock of infrastructure, and its administrative culture, so  $\beta$  is identified from year-to-year variation within states rather than from differences between them.

The model uses state fixed effects only, not a two-way state-and-year design. The reason is substantive: the national pace of deployment is itself policy-driven and is part of what the coefficient is meant to capture, so removing every common-year shock would strip out variation that belongs in the estimate. Contemporaneous reverse causality, the worry that a faster-growing state also installs faster, is handled instead by re-estimating with solar lagged one year,  $\log(\text{Solar})$  at  $t - 1$ , since this year's output cannot have caused last year's capacity.<sup>1</sup> Standard errors are cluster-robust at the state level, computed with the Arellano estimator, which corrects jointly for heteroskedasticity and for the within-state serial correlation confirmed in Section 5.4.

### 5.3 The employment specification

Employment is estimated in the 2022-23 cross-section, for the reason given in Section 4, using the same log-log form for two outcomes, the aggregate Labour Force Participation Rate and the constructed manufacturing employment rate:

$$\log(\text{Emp}_i) = a + b \log(\text{Solar}_i) + u_i$$

Reading the two together is the point: a null on aggregate participation beside a positive coefficient on the manufacturing rate is the pattern the design is built to detect, not a discrepancy to reconcile.

### 5.4 Diagnostics

Two tests accompany the panel. An F-test of the joint significance of the state fixed effects establishes that the intercepts are doing real work rather than absorbing noise, and a Wooldridge test checks for first-order serial correlation in the

residuals. The second is not a formality: its outcome is what justifies the cluster-robust errors used above, rather than leaving them as an assumption.

## 6. Results

### 6.1 Output

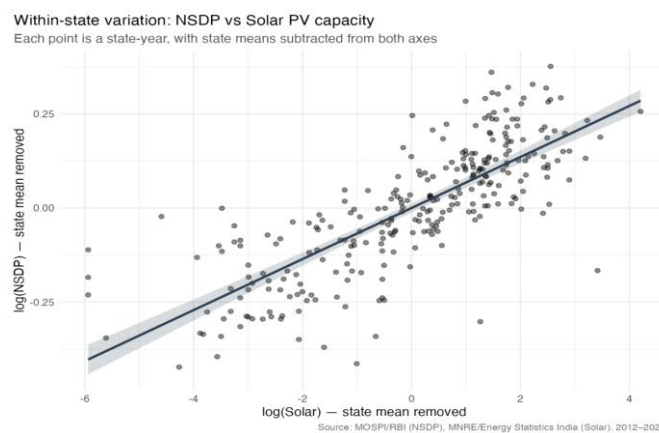
The benchmark from Section 5.1 put the cross-sectional elasticity at 0.572. Once state fixed effects absorb the between-state differences, it falls to 0.068 (Table 3, column 1), significant at the one per cent level ( $t = 9.09$ ), with a within  $R^2$  of 0.61. The collapse is the point: roughly seven-eighths of the raw association was the between-state heterogeneity the panel is designed to remove, and what survives is a within-state elasticity, the response of a state's own output to its own capacity. A single one per cent rise in capacity moves output only a little, but the states in question multiplied their capacity many times over the study window, so the accumulated association is far from trivial. Lagging solar by one year barely moves the estimate, to 0.061 (column 2), and the two confidence intervals overlap across almost their whole length. Since this year's output cannot have caused last year's installed capacity, the stability under lagging is evidence that contemporaneous reverse causality is not what is generating the result. Figure 3 shows the within-transformed data directly: with each state's own time mean removed from both axes, the upward tilt is the within-state relationship, and it is not driven by a handful of extreme state-years. The diagnostics support the specification. The state fixed effects are jointly significant ( $F = 793.46$ ), so pooling the states would discard real variation, and the Wooldridge test rejects the null of no first-order serial correlation, which is what the cluster-robust errors are there to handle.

<sup>1</sup>A national ARIMA(0,1,0) with drift, fitted to annual all-India solar generation over the study window, indicates a steady upward trend of about 3,344 MW per year, so the within-state coefficient is identified off variation around a rising aggregate rather than a flat one.

**Table 3.**Panel fixed-effects estimates: log(NSDP) on log(Solar), 28 states, 2012–2023.

|                     | (1) One-way state FE | (2) FE + lagged solar |
|---------------------|----------------------|-----------------------|
| log(Solar)          | 0.068*** (0.0075)    |                       |
| log(Solar), $t - 1$ |                      | 0.061*** (0.0070)     |
| State fixed effects | Yes                  | Yes                   |
| Within $R^2$        | 0.61                 | 0.59                  |
| States              | 28                   | 28                    |
| Observations        | 285                  | 257                   |

Cluster-robust standard errors (clustered by state) in parentheses. \*\*\*  $p < 0.01$ . For the headline estimate,  $t = 9.09$  and the 95% confidence interval is  $[0.053, 0.082]$ .

**Figure 3.**Within-state relationship between NSDP and solar capacity. Each point is a state-year with the state's own time mean removed from both axes; the fitted slope is the fixed-effects elasticity.

## 6.2 Employment

The employment cross-section splits along the line Section 2.3 anticipated (Table 4). On the aggregate side there is nothing: the elasticity of the Labour Force Participation Rate with respect to solar capacity is essentially zero and statistically insignificant ( $\beta = -0.010$ ,  $p = 0.262$ ), the cleanest possible null. A state's installed capacity carries no detectable relationship with how much of its working-age population is in the labour force.

The manufacturing rate behaves differently. Its elasticity is 0.129, significant at the one per cent

level, so a state with twice the installed capacity of another has, on average, about nine per cent higher manufacturing employment as a share of its working-age population (Figure 4). The cross-sectional design cannot rule out that some of this reflects the industrial character of the states that deploy most, and the looser fit here than in the output regression is consistent with that. But the contrast between the two employment outcomes is the one the design was built to detect: no signal in the aggregate, a clear one in the sector where solar's labour actually sits.

**Table 4.**Cross-sectional employment estimates, 2022–23 (log-log specification).

|                       | Labour Force Participation Rate | Manufacturing employment rate |
|-----------------------|---------------------------------|-------------------------------|
| log(Solar)            | -0.010 (0.0085)                 | 0.129*** (0.0350)             |
| t-value               | -1.15                           | 3.69                          |
| p-value               | 0.262                           | 0.001                         |
| $R^2$                 | 0.05                            | 0.34                          |
| Observations (states) | 28                              | 28                            |

Ordinary least squares on the 2022-23 cross-section; dependent variables and solar capacity in logs. Standard errors in parentheses. \*\*\*  $p < 0.01$ .

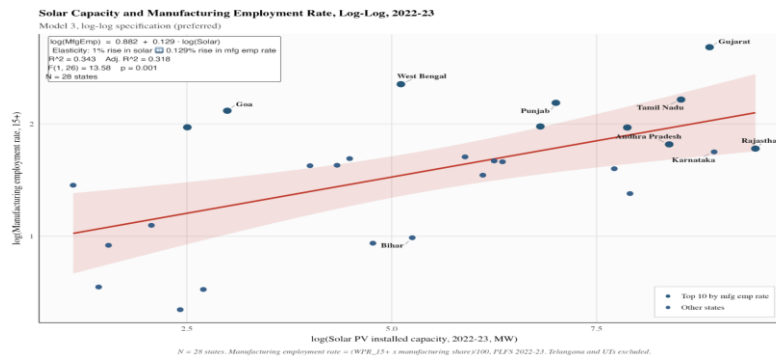


**Figure 4.** Solar capacity and the manufacturing employment rate across states, 2022–23 (log-log). The fitted line is the cross-sectional elasticity of 0.129.

## 7. Discussion

### 7.1 Output: a real signal

Read across the specifications, the output result is consistent in a way that is hard to dismiss. The cross-section, the panel, and the lagged panel point the same direction, and the estimate that is hardest to explain away, the lagged within-state one, is also the one that survives the most demanding adjustment. The size sits comfortably alongside the international evidence that isolates solar (Liao et al., 2025) and with the endogenous-growth prediction that a solar transition lifts output through cheaper energy and reallocated capital rather than through the headline investment figure (Court, Jouvett and Lantz, 2018). It matches the Indian panels that pool renewables and reach a positive conclusion (Bhavsar, Bendigiri and Samanta, 2025), while adding what those cannot report: an elasticity for grid-connected solar on its own. The one qualification worth stating plainly is that the estimate is driven mainly by the handful of states that deployed heavily, so it need not carry over to states that have barely deployed. The response is identified mostly off the achiever cluster, and nothing here shows that the marginal, barely-deploying states would earn the same return, a limit consistent with the threshold and absorptive-capacity findings in the wider literature.

### 7.2 Employment: the aggregate null and the sectoral signal

The employment result is more interesting for being split. The aggregate null is not a failure to find an effect so much as a finding in its own right: at the scale solar has reached in India, deployment does not move a state's overall participation rate, which is what a net-employment literature built around displacement and small steady-state footprints would lead one to expect (Stavropoulos and Burger, 2020; Hanna, Heptonstall and Gross, 2024). The manufacturing signal is the other half of the same prediction. In equipment, construction, and maintenance the effect does register, and at a size that is economically visible even in a single cross-section. Lehr, Lutz and Edler (2012) document precisely this asymmetry for Germany, a modest aggregate effect beside a measurable manufacturing one, and the Indian cross-section reproduces it. The two results together say that the labour question has often been asked at the wrong level: the effect is real but sectoral, and it dissolves when averaged into a headline participation rate.

### 7.3 Interpreting the split

The uncomfortable part, for the narrative that has sold solar as an employment programme, is that growth and jobs come apart. Deployment lifts output, and it lifts manufacturing employment, but it leaves the aggregate labour market untouched, because once a project is built it needs very little ongoing labour. A single study cannot settle whether this is because the underlying assumption is wrong or because the sectoral footprint is real but too small to surface in a participation rate of tens of

millions. What it can say is that the two readings carry very different implications, and that the places to look next, the localisation of manufacturing, the durability of construction-phase work, and the design of the schemes that route deployment to particular sectors, are clear enough. The output case for solar is well supported by this data; the aggregate-jobs case is not, and treating it as settled risks promising what the technology, on this evidence, does not deliver.

## 8. Conclusion and policy implications

This paper set out to look at solar deployment and the economies of India's states together, output and employment in one frame instead of one at a time. Across the 2012 to 2023 panel, a state's real NSDP rises with its own installed solar capacity, and that link survives when capacity is lagged by a year. Employment is where the picture splits. The aggregate labor force participation shows no association with the installed solar capacity whereas the manufacturing employment rate, in the 2022-23 cross-section, shows a positive association

The reading has to be careful. If the labour gains are real, they sit in certain sectors and certain links of the renewable-energy value chain rather than the entire workforce at large, which is why India's solar expansion should not be judged by the aggregate labor force indicators. However, the reading should be done carefully. The cross-sectional nature of the employment analysis and the limited causal identification of the output model means the estimates are best interpreted as associations rather than as causal effects, identified mainly off the states that deployed most heavily. That caution does not drain the findings of policy content. If the output gains have to be converted into real gains, the groundwork has to be laid first: transmission and storage to carry the power, distribution companies solvent enough to pay for it, and renewable purchase obligations that are enforced and not merely announced. And if the jobs effect is sectoral, the tools that answer it should be sectoral too, nearer to the Production-Linked Incentive scheme and the skilling behind it than to any pledge of employment in the aggregate.

Further research scope points to instruments which can sharpen the identification. Richer time-varying

controls, alternative measures of deployment, state-specific trends, instrumental-variable strategies, and district-level data matched to households can be implemented. Together they would show whether what this paper records as association is in fact causal, and how that answer shifts across regions and differing industrial structures.

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