



RESEARCH ARTICLE

Green Economy Transition and its Impact on Employment Generation and Economic Sustainability: A Stochastic Multi-Module Simulation of India's Power and Green-Hydrogen Transition to 2050

*Mr. Aman Bhargava

*Assistant Professor, Parul University, Vadodara, Gujarat. aman24bhargava@gmail.com

ABSTRACT

The prognosis for employment is encouraging in the Green Economy, but only scant and deterministic proof can be found for such large emerging economies like the China Coal Economy. The present study creates GEMSIM-IN, a stochastic model that combines the technology-specific employment factors, coal value chain and macro-accounting, power dispatch, and India 2025 data. Three options – Current Policies (S1), Announced Targets (S2), and an Accelerated Just Green Transition (S3) – are compared for 2050. Entropy-weighted Green Economy Sustainability Index (GESI) and TOPSIS are used to rank scenarios, 10,000 Monte Carlo draws and Sobol indices are used to propagate uncertainty on 21 parameters, and the change in employment is broken down using a logarithmic mean Divisia index (LMDI). Compared to S1, S3 generates 5.61 million additional energy-sector job-years (Monte Carlo mean 6.47 million, 90% interval –2.40 to 15.96, probability of a positive outcome 0.88), increases GDP by 0.66% in 2040 and avoids 21.6 Gt CO₂. The employment dividend, however, is frontloaded, with maximum net gains still reaching 483 000 jobs in 2032, but losses being recorded after 2045 when construction activity matures, learning reduces its labour intensity, and construction activity displaces labour-intensive coal mining. Rooftop and distributed solar have the highest \$JY/USD million of capital expenditure and account for 58% of the variance in output, due to the green multiplier, the informality of coal work and the labor-productivity learning rate. The net losses are now in the states of Odisha, Chhattisgarh and Jharkhand. S3 ranks first on the GESI (0.750) and TOPSIS (closeness 0.799). Distributed solar energy, in coal regions, just-transition investment and domestic clean energy manufacturing are needed to keep jobs.

Keywords: Green economy, Green jobs, Just transition, Inclusive transition, India, Energy transition, Employment factors, Sustainability index, Monte Carlo Simulation

INTRODUCTION

What was once an aspiration, namely using the concept of what is called "green economy"—growth in income and employment resulting from investment that reduces carbon emissions and pollution, enhances resource use efficiency, and prevents damage to ecosystem services, has now become a key organising principle of economic policy (UNEP, 2011; OECD, 2011). From a political standpoint, it has a double-dividend argument: that decarbonisation will not necessarily result in job losses, but will instead spur job growth and ongoing prosperity (Barbier, 2010; Pollin, 2015). The ILO estimated that a Paris Agreement-aligned transition could be associated with the creation of around 24 million jobs worldwide by 2030 and associated with the loss of about 6 million jobs (ILO, 2018), and an increasing number of renewable-energy jobs is estimated at 16.6 million in 2024 (IRENA and ILO, 2025).

*Assistant Professor, Parul University, Vadodara, Gujarat.

Email-id: aman24bhargava@gmail.com

Corresponding Author: Mr. Aman Bhargava

Assistant Professor, Parul University, Vadodara, Gujarat..

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The link between greening and jobs is therefore neither automatic nor continuous over time.

The impact of this tension is most important in large, rapidly expanding, coal-heavy emerging economies. The most obvious example is in India. It is the third-largest emitter, coal still accounts for about 70% of electricity generation and domestic coal output is expected to breach 1 billion tonnes for the first time in 2024-25, as per the Ministry of Coal (2026). Meanwhile, India has also seen record installations of solar (37.9 GW) and wind (6.3 GW) energy during calendar 2025, bringing cumulative renewable energy generation to approximately 258 GW (data from MNRE reported by PV Magazine, 2026). India's revised NDCs include plans to increase non-fossil installed capacity to 50% by 2030 and achieve net zero by 2070 (Government of India, 2022), and the government is also looking for additional coal-based capacities to achieve base-load security (CEA, 2023). The stakes on the labour market side are high, as there are approximately 337,000 workers directly employed in the formal sector of coal mining and many times that number in informal and indirect livelihoods in coal areas, which are among the poorest in the country (GEM, 2023; IISD, 2019).

There are 3 strands to the literature of relevant evidence and important gaps. Employment-factor studies measure the number of jobs per megawatt invested for each technology and demonstrate that it is more employment-intensive per unit of investment for renewables than for fossil generation (Wei et al., 2010; Cameron and van der Zwaan, 2015; Rutovitz et al., 2015; Ram et al., 2020). IOGE studies, predominantly for Europe and America, find positive net employment results, albeit with indirect and induced effects included (Lehr et al., 2012; Markandya et al., 2016; Garrett-Peltier, 2017; Fragkos and Paroussos, 2018). Just-transition literature highlights that gains and losses are experienced by different workers and in other places (Healy and Barry, 2017; Pai et al., 2020; Jakob et al., 2020). Facilitators for renewable targets are CEEW assessments (2017; 2026) that offer valuable gross estimates of employment, but do not formally capture parameter uncertainty, do not account for the dis-employment of fossil sector jobs or associate employment with macroeconomic and environmental sustainability in a single framework.

Four gaps follow. First, most of the estimates of net-employment are also deterministic, and there is even a factor of two to three difference in the estimates of employment factors between studies on India. Second, few studies model the time evolution of the employment dividend as labor productivity goes up, and the time profile of net jobs is usually not reported, which is important for policy sequencing. Third, green jobs are typically not quantified, and regional job gaps between growth in green and decline in coal are seldom analyzed. Fourth, GDP, emissions and transition costs are hardly ever adopted in a composite assessment of sustainability, making it possible to

transparently rank pathways for employment.

This paper aims to fill these lacunas by creating and functionalizing the Green Economy Employment and Macro-Sustainability Simulation model for India (GEMSIM-IN). It poses 4 research questions. RQ1: What is the net employment impact of the different scenarios of the green transition in India in 2025–2050, with displacement in the coal value chain accounted for? RQ2: What is the robustness of that effect to uncertainty, and which parameters control it? RQ3: How does this impact employment composition (all phases) and geographic distribution of employment (skills, gender)? RQ4: What path comes out best in a composite indicator of economic sustainability that combines the numbers of jobs, growth, emissions, import dependence and transition burden?

The study makes four contributions. Methodologically, it combines the employment factors with a capacity-constrained dispatch and coal value-chain module, as well as with a macro-accounting module, and propagates the whole system via Monte Carlo propagation and variance-based (Sobol) sensitivity analysis. Empirically, it offers the first estimate of India-specific net energy-sector employment in a probabilistic, time-resolved manner for three policy pathways, along with a LMDI decomposition of the drivers of change – in terms of scale, technology-mix and labour-intensity contribution. Geographically, it measures the extent of 'green' gains in a state, relative to the loss of coal jobs, and the magnitude of the 'green'–coal transition-unemployment pool in a particular state. Normally, it implies an introduction of an entropy-weighted Green Economy Sustainability Index (GESI) combined TOPSIS ranking to verify comparison of pathways on objective weights. All model code and outputs are made available for duplication.

The rest of the paper can be organised as follows. The literature review and hypotheses are presented in Section 2. The model, data, scenarios and analytical methods are presented in section 3. The Results are reported in Section 4. These are discussed in relation to other work in Section 5, and policy implications are stated whilst limitations are pointed out. Section 6 concludes.

2. Literature review and hypotheses

2.1. Green economy, green growth and the employment question

The green-growth literature suggests that higher investment demand in the short run, innovation and efficiency in the long run and the reductions in damages due to pollution and climate change could all contribute to an increase in output as a result of environmental policy (Hallegatte et al., 2012; Jacobs, 2012; Stern, 2007). In these arguments, employment plays a pivotal role in the political economy. In addition to stimulating domestic manufacturing capacity and job creation (Green Industrial Policy), the policy is also justified for avoiding the trade of renewables, while the other side of the argument

suggests that they may be subjected to an increase in energy costs regarding transition costs as well as the loss of well-paying jobs in the fossil fuel industry (Crowding-out). Decoupling literature provides a long-run perspective: rising income should also lead to a decline in emissions, i.e., absolute, rather than relative decoupling, and the environmental Kuznets curve hypothesis argues that such absolute decoupling is only achieved at higher income levels (Tapio, 2005; Grossman and Krueger, 1995).

2.2. Methods for estimating employment effects

Three groups of methods predominate. Employment-factor (bottom-up) models multiply the number of capacity additions and stocks by the jobs per megawatt for construction, manufacturing and operation (Wei et al., 2010; Rutovitz et al., 2015; Ram et al., 2020). They are "transparent" and are very information- and technology-intensive; however, they only reflect "direct" roles if the multipliers are included. Input–output models account for indirect influences via supply chains and induced responses through income spending: Garrett-Peltier (2017) estimated that an additional ~5 jobs are generated in the USA in response to each \$1 million of fossil fuel capital switches to renewables/efficiency. Price and labour-supply and crowding-out effects are added in computable general equilibrium and macro-econometric models, and tend to make for smaller net effects (Lehr et al., 2012; Fragkos and Paroussos, 2018). As presented in Cameron and van der Zwaan (2015), published employment factors for wind and solar are quite varied, with both types of factors decreasing over time, and are preclusive of explicitly treating uncertainty and learning.

2.3. Skills, composition and just transition

Green jobs have specific skill components, different from other jobs: they require more abstract skills, engineering and technical skills (Consoli et al., 2016; Vona et al., 2018) and greening alters the composition of skills within occupations

(Bowen et al., 2018). These differences suggest that it is not a simple matter to plug fossil-fuel workers into green jobs. The just-transition framework (ILO, 2015) thus raises the question of which groups of workers and regions are affected by the losses. Lienerth et al. (2019) discuss how this view neglects the political aspects of transitions, while Healy and Barry (2017) point to the geographical focus of coal dependence in regions or states, as is, for instance, the case with the German transition. However, Jakob et al. (2020) demonstrate that for India, solar resources are better situated than wind resources, both from the perspective of the geographical impact of coal mining and also from the possibility of local re-employment. On a global scale, Pai et al. (2021) project net positive increases in overall employment in the energy sector through a well-below-2 °C pathway, with employment growth in solar and wind outcompeting declines in fossil extraction, storage and processing, pipeline and electrical grid infrastructure, conventional combustion equipment, and manufacturing.

2.4. Evidence for India and research gap

Gross estimates predominate in India. Rooftop solar PV is estimated to create 24.72 job-years per MW, compared to ground-mounted solar PV and wind at 3.45 and 1.27 job-years per MW, respectively (CEEW and NRDC, 2017). A subsequent study based on surveys emailed to sick industries instead indicated employment factors of around 45, 1 and 0.6 job-years per MW for rooftop solar, ground-mounted solar and wind, respectively, projecting over 4.4 million full-time-equivalent (FTE) jobs from India's 2030 clean-energy goals (CEEW and NRDC, 2026). Fossilwise, Global Energy Monitor estimated potential job losses in Coal India of some 73,800 direct jobs by 2050 along a 1.5 °C-aligned pathway (GEM, 2023). Table 1 summarises representative studies. None does (i) net accounting of green gains, (ii) 'formal uncertainty' and variance decomposition, (iii) temporal decomposition of employment drivers, (iv) regional mismatch and (v) composite sustainability ranking for India.

Table 1. Summary of representative studies on green transition and employment.

Study	Scope	Method	Main finding	Limitation addressed here
Wei et al. (2010)	USA	Employment factors	RE and efficiency more job-intensive than fossil per unit energy	Static factors; no uncertainty
Lehr et al. (2012)	Germany	Macro-econometric	Small positive net employment	High-income context
Cameron and van der Zwaan (2015)	Global	Literature review	Wide variation and decline of factors	No net or regional analysis
Markandya et al. (2016)	EU	Multi-regional I–O	Low-carbon technologies created net jobs 1995–2009	Historical, not prospective
Garrett-Peltier (2017)	USA	Input–output	~5 net jobs per US\$1 M shifted to green	Single country; deterministic

Fragkos and Paroussos (2018)	EU	CGE (GEM-E3)	Modest net gains from RE expansion	Equilibrium assumptions
Ram et al. (2020)	Global	Employment factors, 100% RE	Energy jobs rise to 2050	Global aggregation
Pai et al. (2021)	Global	IAM + factors	Well-below 2 °C raises energy jobs	Coarse regional detail
CEEW and NRDC (2017; 2026)	India	Survey-based factors	>4.4 M FTE from 2030 goals	Gross only; no displacement
GEM (2023)	Global/India	Mine-level tracker	73,800 Coal India jobs at risk by 2050	Coal side only
This study	India	Stochastic multi-module	Net, time-resolved, regional and composite	–

Based on this literature, five hypotheses are tested.

- **H1.** An accelerated green transition yields positive cumulative net energy-sector employment in India relative to current policies.
- **H2.** The net employment dividend is transitional: it declines over time as construction activity matures and employment factors fall.
- **H3.** Distributed (rooftop and agricultural) solar is the most labour-intensive green technology per unit of investment.
- **H4.** Employment gains and losses are spatially mismatched, with net losses concentrated in coal-producing states.
- **H5.** The green transition raises GDP and improves composite economic sustainability relative to current policies.

3. Materials and methods

3.1. Modelling framework

The GEMSIM-IN ECB is a yearly, scenario-based simulation model for the years 2025–2050 (Fig. 1). Module A applies technology- and phase-specific employment factors that decrease with learning to relate capacity additions, capacity stocks and domestic production to full-time equivalent (FTE) employment. Module B spreads the common electricity demand over the technologies that fall within the coal fleet load-factor boundaries and converts coal generation to coal production and coal mining jobs. Module C calculates the value of investment, the deviation of GDP values, CO₂ emissions and externality values. A sub-module for the labour pool is developed for the tracking of coal workers forced to move. All the modules are vectorised - the same code is used to execute the deterministic case, Monte Carlo propagation and analysis by the Sobol method. As the model is based on published model adjustments and pathways, the results are in-silico data and can be traced back to the published code.

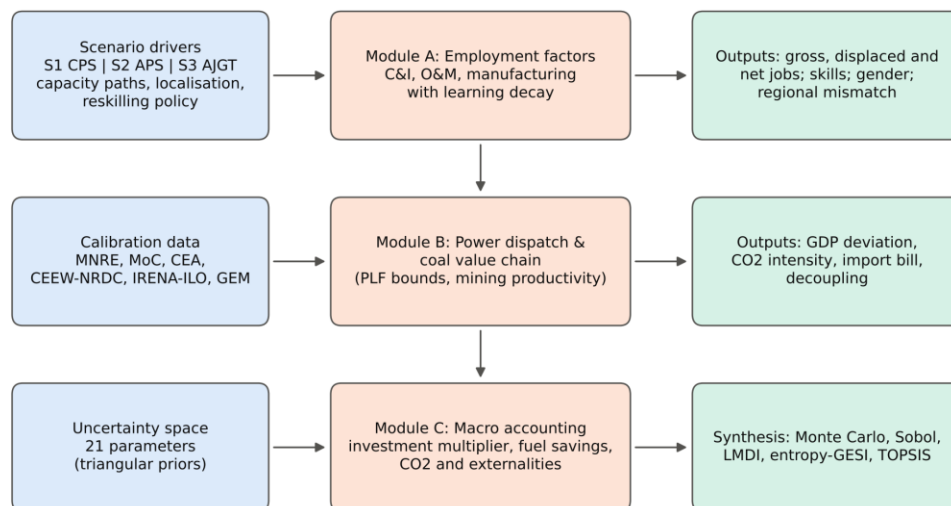


Fig. 1. Analytical framework of GEMSIM-IN, showing scenario drivers and data inputs, the three model modules, and the outputs and synthesis methods.

3.2. Scenarios

There are three pathways defined (Table 2). All demand the same exogenous electricity demand (1,830 TWh in 2025 increasing to 4,850 TWh in 2050), the same generation from hydro, nuclear and bioenergy and the same baseline GDP path (US\$4.0 trillion by 2025, 6.5% to 2030, 6.0% to 2040 and 5.0% to 2050). This means that the only differences between the different scenarios are determined by technology deployment, coal-fleet evolution, localization of manufacture,

non-power coal demand and the effectiveness of reskilling policy. S1 continues the policies in place, such as the projected ramp-up of coal supply to approximately 307 GW by 2035 (CEA, 2023). S2 is adequate to achieve the 2030 non-fossil goal and maintains steady progress. S3 puts an emphasis on the loading capacity of coal near 2030, the active skills training programme, and pre-focusing on distributed solar PV and local manufacturing. Year-end capacity points are interpolated using a monotone piecewise cubic (PCHIP) spline.

Table 2. Scenario definitions (year-end capacity anchors and policy levers).

Lever	S1: Current Policies (CPS)	S2: Announced Targets (APS)	S3: Accelerated Just Green Transition (AJGT)
Solar PV, 2030 / 2050 (GW)	230 / 550	300 / 1,050	335 / 1,500
of which rooftop + distributed, 2050 (GW)	165	330	520
Onshore wind, 2030 / 2050 (GW)	85 / 200	100 / 330	110 / 400
Battery storage, 2050 (GWh)	400	1,000	1,600
Electrolysers, 2030 / 2050 (GW)	5 / 40	15 / 120	25 / 200
Coal + lignite capacity, 2035 / 2050 (GW)	307 / 360	285 / 230	230 / 120
Domestic share of PV supply	60%	80%	95%
PV module exports from 2027 (GW/yr)	5	10	25
Non-power coal demand growth	+3.0%/yr	+2.0%/yr to 2035, flat after	+1.5%/yr to 2035, -2.0%/yr after
Annual re-absorption rate of displaced workers	15%	25%	45%

Capacity values are scenario anchors; in the simulation, capacity above the S1 path is scaled by the deployment realisation factor (base 0.95).

3.3. Module A: employment factors with learning

For technology i in year t , direct construction-and-installation (C&I), operation-and-maintenance (O&M) and manufacturing (MFG) employment are

$$J_{i,t}^{CI} = \Delta K_{i,t} \cdot e_{i,t}^{CI} \cdot (1 - \lambda)^{t-t_0} \quad (1)$$

$$J_{i,t}^{OM} = K_{i,t} \cdot e_{i,t}^{OM} \cdot (1 - \lambda)^{t-t_0} \quad (2)$$

$$J_{i,t}^{MFG} = (\delta_i \Delta K_{i,t} + X_{i,t}) \cdot e_{i,t}^{MFG} \cdot (1 - \lambda)^{t-t_0} \quad (3)$$

where ΔK is gross capacity added (MW), K the installed stock, e the employment factor (job-years per MW for C&I and MFG; FTE per MW for O&M), δ the domestic supply share, X module exports and λ the annual decline of employment factors through automation and scale economies, as documented by IRENA and ILO (2025). Rooftop and distributed solar are assigned twice the utility O&M factor. Green-hydrogen hubs include electrolyser C&I and O&M plus 1.5 GW of dedicated

off-grid renewable capacity per GW of electrolyser, and grid employment is 0.6 job-years per MW of variable renewable energy (VRE) added. Battery employment is applied per MWh with a localisation-weighted manufacturing component.

3.4. Module B: dispatch and coal value chain

Annual coal generation is the residual demand after VRE (on mid-year capacity and fixed capacity factors), other clean generation and gas, bounded by minimum and maximum plant load factors $\varphi_{\min} = 0.30$ and $\varphi_{\max} = 0.85$:

$$G_t^c = \min \{ \max [D_t - \sum_i CF_i \bar{K}_{i,t} h - G_t^{oc} - G_t^{gas}, \varphi_{\min} \bar{K}_{c,t} h], \varphi_{\max} \bar{K}_{c,t} h \} \quad (4)$$

Residual demand below the minimum bound would imply VRE curtailment and above the maximum bound unserved energy; neither occurs in any scenario, confirming internal consistency of the pathways. Domestic coal production combines power-sector use (specific consumption $\sigma = 0.66$ Mt/TWh) and non-power demand Q^{np} , net of an import share $\mu = 0.12$. Formal mining employment uses the 2024–25 ratio of workers to output, $\pi_0 = 322$ jobs/Mt, declining at labour-productivity growth ρ , and informal employment is a multiple ω of formal

jobs:

$$Q_t = (1 - \mu)(\sigma G_t^c + Q_t^{np}), \quad J_t^{\text{mine}} = Q_t \cdot \pi_0 (1 - \rho)^{t-t_0} (1 + \omega) \quad (5)$$

Coal-plant O&M employment is proportional to installed capacity and declines at the same productivity rate; new coal capacity requires 2.5 job-years per MW to build. Total energy-sector employment applies separate Type II (indirect plus induced) multipliers m_g and m_c to green and coal direct jobs:

$$J_t^{\text{tot}} = (1 + m_g) \sum_g J_{g,t}^{\text{dir}} + (1 + m_c) \sum_c J_{c,t}^{\text{dir}} \quad (6)$$

3.5. Module C: macro-accounting, emissions and externalities

Investment is capacity added times unit capital cost, with real cost declines (e.g., utility solar from US\$0.45 M/MW at 3%/yr, batteries from US\$0.20 M/MWh at 5%/yr, electrolyzers from US\$0.90 M/MW at 6%/yr, with floors). The GDP deviation of scenarios relative to S1 combines a demand-side investment effect and a supply-side energy-cost effect:

$$\Delta Y_{s,t} = k(1 - \theta) \Delta I_{s,t}^{\text{dom}} + \Delta F_{s,t} - \Delta C_{s,t}^{\text{int}} + 0.5 \Delta M_{s,t} \quad (7)$$

where k is the investment multiplier, θ the crowding-out share, ΔI^{dom} the change in domestically retained investment (40% local works plus 60% equipment scaled by the domestic supply share), ΔF avoided coal fuel cost (US\$35/MWh rising 1%/yr), ΔC^{int} additional VRE integration cost (US\$5/MWh plus US\$20/MWh per unit of VRE share above 30%) and ΔM the change in the coal import bill (US\$90/t). Power-sector CO₂ uses 0.96 tCO₂/MWh for coal and 0.40 tCO₂/MWh for gas; each tonne of green hydrogen displaces 10 tCO₂ from grey hydrogen. Externality benefits value avoided CO₂ at the social cost of carbon and avoided coal generation at an air-pollution

damage rate. Externalities are reported separately and are not added to GDP.

3.6. Just-transition labour pool

Coal workers displaced in year t are the decline in coal employment beyond natural attrition $a = 2.5\%/yr$ (retirements); the stock of transition-unemployed workers U is re-absorbed at a scenario-specific rate r that reflects the strength of reskilling and placement policy (Table 2):

$$U_t = (1 - r) U_{t-1} + \max[(1 - a) W_{t-1} - W_t, 0] \quad (8)$$

A reskilling budget is estimated at US\$3,000 per displaced worker, an assumption informed by public training-programme costs.

3.7. Data, calibration and parameter uncertainty

Coal-workforce data, employment factors, Coal output, additions, and base-year capacity are from MNRE, Ministry of Coal, Central Electricity Authority (2017; 2026), Rutovitz et al. (2015), and Ram et al. (2020). The 21 uncertain parameters are assigned triangular distributions, which include the published range (Table 3). The base case is with the modes. Table 4 summarises the results of the calibration against 2025 observations: by construction, the capacity variables match, and the coal production is within 8% of the observed value, as is also the case for the coal-fleet load factor, and the formal value of mining employment. Modelled power-sector CO₂ is higher than the most recent official estimate of 1.10 Gt for 2022-23, which is in line with increases in coal generation since this period.

Table 3. Uncertain parameters, triangular distributions and sources.

Parameter	Symbol	Min	Base (mode)	Max	Unit	Basis / source
Utility solar C&I factor	ef_us_ci	1	1.8	3.45	job-yr/MW	CEEW-NRDC 2017; 2026
Rooftop solar C&I factor	ef_rts_ci	12	22	45	job-yr/MW	CEEW-NRDC 2017; 2026
Distributed/agri-solar C&I factor	ef_ds_ci	6	10	18	job-yr/MW	CEEW-NRDC 2026 (PM-KUSUM)
Wind C&I factor	ef_wind_ci	0.6	1	1.6	job-yr/MW	CEEW-NRDC 2017; 2026
Solar O&M factor (utility)	ef_om_pv	0.15	0.3	0.5	FTE/MW	Rutovitz et al. 2015; Ram et al. 2020
Wind O&M factor	ef_om_wind	0.15	0.25	0.4	FTE/MW	Rutovitz et al. 2015; Ram et al. 2020
PV manufacturing factor	ef_mfg_pv	0.8	1.5	2.5	job-yr/MW	CEEW-NRDC 2017; Ram et al. 2020
Wind manufacturing factor	ef_mfg_wind	0.8	1.5	2.5	job-yr/MW	Rutovitz et al. 2015
Battery storage factor	ef_bess	0.08	0.15	0.3	job-	Ram et al. 2020

					yr/MWh	
Electrolyser C&I factor	ef_h2	1	1.8	3	job-yr/MW	IRENA 2025; assumption
Employment-factor decline rate	learn	0.01	0.025	0.04	yr ⁻¹	IRENA 2025 (automation); assumption
Coal labour-productivity growth	coal_prod	0.015	0.025	0.04	yr ⁻¹	Coal India productivity trend
Informal-to-formal coal ratio	informal	1	1.5	3	ratio	GEM 2023; IISD 2019
Coal plant O&M factor	ef_coal_om	0.3	0.45	0.7	FTE/MW	CEA staffing norms; assumption
Indirect+induced multiplier, green	mult_green	0.4	0.8	1.4	ratio	Garrett-Peltier 2017; Markandya et al. 2016
Indirect+induced multiplier, coal	mult_coal	0.4	0.8	1.4	ratio	Garrett-Peltier 2017
Deployment realisation factor	deploy	0.8	0.95	1.05	ratio	Policy delivery risk; assumption
Investment multiplier	k_inv	0.8	1.3	1.8	ratio	Fiscal/investment multiplier literature
Crowding-out share	crowd	0	0.3	0.5	share	Crowding-out; assumption
Social cost of carbon	scc	25	50	150	USD/tCO2	IPCC AR6; EPA 2023
Air-pollution damage	health	10	25	45	USD/MWh coal	Air-pollution damage literature

Table 4. Base-year (2025) calibration of GEMSIM-IN against observed indicators.

Indicator (base year 2025)	Observed	Modelled	Deviation (%)	Source
Solar + wind installed capacity (GW, Dec-2025)	190.0	190.0	+0.0	MNRE via JMK/pv magazine (2026)
Solar capacity additions, CY2025 (GW)	37.9	37.8	-0.3	MNRE via pv magazine (2026)
Wind capacity additions, CY2025 (GW)	6.30	6.30	-0.0	MNRE via pv magazine (2026)
Domestic raw coal production (Mt, FY2024-25)	1,047.5	985.1	-6.0	Ministry of Coal (2026)
Coal-fleet plant load factor (-)	0.69	0.64	-7.5	CEA (approx., FY2024-25)
Formal coal-mining workforce (persons)	337,400.0	317,297.5	-6.0	GEM (2023)
Power-sector CO2 (Mt)	1,100.0	1,207.9	+9.8	CEA (FY2022-23; rising)

3.8. Uncertainty propagation and variance-based sensitivity

Uncertainty is propagated with 10,000 Monte Carlo draws, using common random numbers across scenarios so that differences reflect policy rather than sampling noise. Global sensitivity is quantified with Sobol indices (Sobol', 2001). The first-order index S_j measures the share of output variance explained by parameter j alone, and the total-order index S_{Tj} includes all its interactions:

$$S_j = V[E(Y | X_j)] / V(Y), \quad S_{Tj} = E[V(Y | X_{-j})] / V(Y)$$

(9)

They are estimated with the Saltelli et al. (2010) estimator for S_j and the Jansen (1999) estimator for S_{Tj} , using $N = 8,192$ base samples (196,608 model evaluations per output), centred outputs and 200 bootstrap replicates for 95% confidence intervals. Two outputs are analysed: cumulative net job-years in S3 relative to S1 and the GDP deviation in 2040.

3.9. LMDI decomposition

Direct green employment J is decomposed into investment scale I , technology mix $s_i = I_i/I$ and labour intensity $\iota_i = J_i/I_i$ across five technology groups using the additive LMDI-I method (Ang, 2005, 2015), which leaves no residual:

$$\Delta J = \sum_i L(J_i^T, J_i^0) [\ln(I^T/I^0) + \ln(s_i^T/s_i^0) + \ln(\iota_i^T/\iota_i^0)] \quad (10)$$

where $L(a, b) = (a - b)/(\ln a - \ln b)$ is the logarithmic mean.

3.10. Green Economy Sustainability Index and TOPSIS

The following six indicators are a core component of a sustainable green economy: (1) overall employment in the energy sector, (2) gross domestic product deviation, (3) CO₂ intensity in the power generation sector, (4) share of clean energy generation, (5) coal import bill and (6) transition-unemployment pool. Indicators are min-max normalised (z_{ij} , reversed for cost-type indicators), weighted objectively by Shannon entropy (Shannon, 1948) which assigns higher weight to indicators that have greater discriminatory power between alternatives, for 15 alternatives (three scenarios and five

milestone years):

$$e_j = -(1/\ln n) \sum_i p_{ij} \ln p_{ij}, \quad w_j = (1 - e_j) / \sum_j (1 - e_j), \quad \text{GESI}_i = \sum_j w_j z_{ij} \quad (11)$$

The 2050 outcomes are also ranked with TOPSIS (Hwang and Yoon, 1981) using vector normalisation and the same weights; the closeness coefficient is $C_i = D_i^- / (D_i^+ + D_i^-)$, where D_i^+ and D_i^- are distances to the ideal and anti-ideal solutions.

4. Results

4.1. Technology pathways and power-system outcomes

Fig. 2 shows the deployment pathways. Solar capacity reaches 550 GW in S1, 1,025 GW in S2 and 1,453 GW in S3 by 2050, and coal capacity diverges after 2030, rising to 360 GW in S1 but falling to 120 GW in S3. The clean share of generation rises from 30% in 2025 to 45% (S1), 66% (S2) and 83% (S3) in 2050. Because demand grows 2.7-fold, coal generation still doubles in S1, to 2,529 TWh, and remains broadly flat in S2; only in S3 does it fall in absolute terms, to 758 TWh (Fig. 3). Power-sector CO₂ intensity falls from 517 g/kWh in S1 to 317 g/kWh in S2 and 155 g/kWh in S3 by 2050 (Table 5).

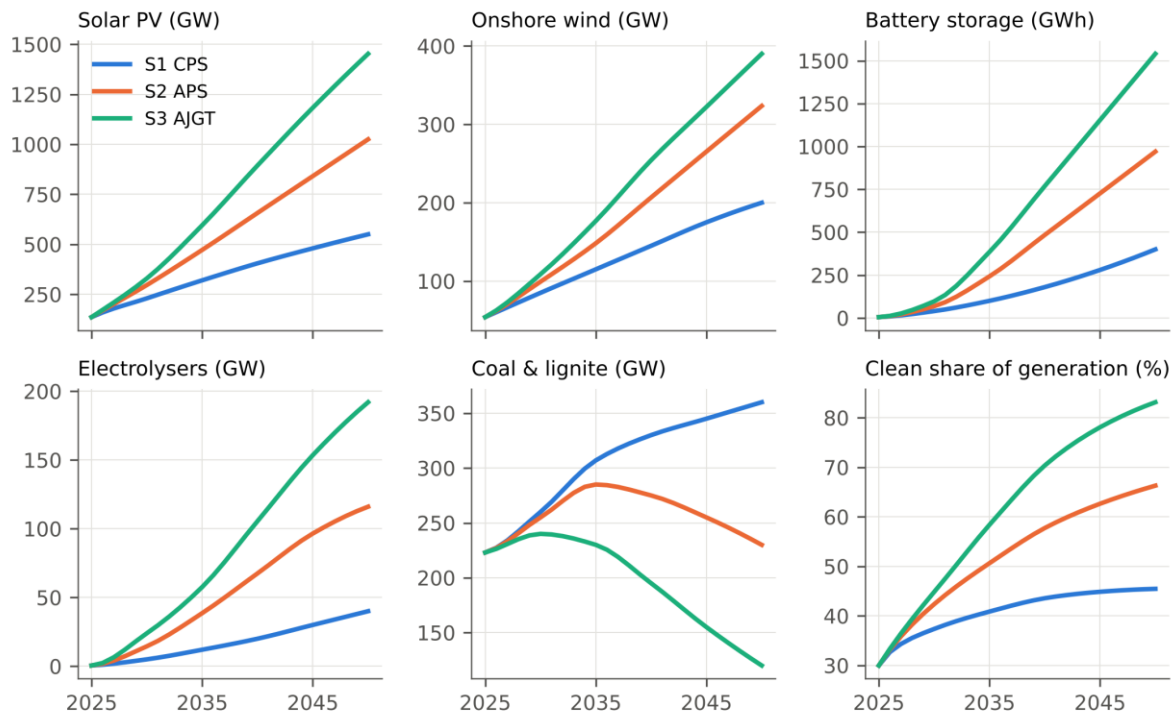


Fig. 2. Installed-capacity pathways for solar PV, onshore wind, battery storage, electrolysers and coal, and the resulting clean share of electricity generation, 2025–2050.

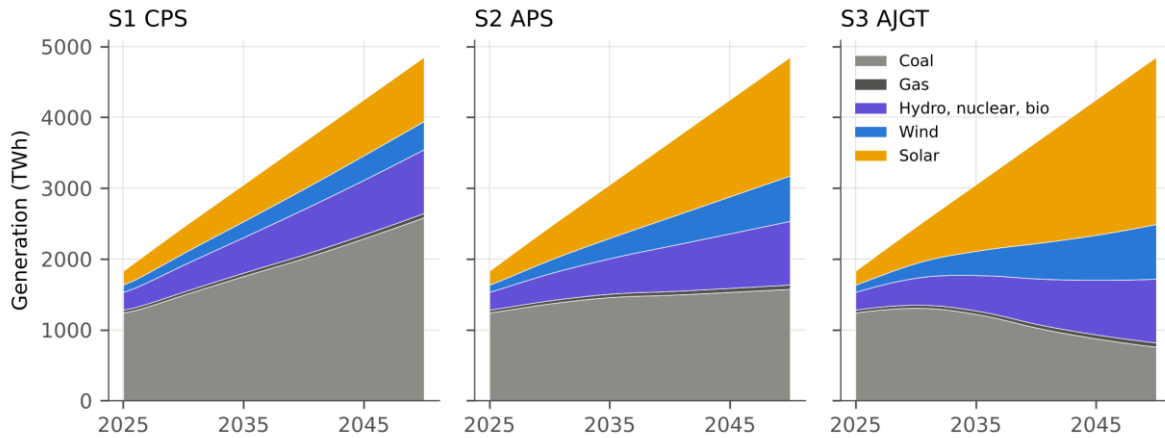


Fig. 3. Electricity generation mix by scenario, 2025–2050. Demand is identical across scenarios; differences reflect deployment and coal-fleet pathways.

Table 5. Key system, employment and macroeconomic outcomes by scenario (base case).

Scenario	Year	Solar (GW)	Wind (GW)	Coal (GW)	Clean gen. share (%)	Power CO ₂ (Mt)	CO ₂ intensity (g/kWh)	Green direct jobs (k)	Coal direct jobs (k)	Total energy jobs* (k)	Net vs S1 (k)	Green capex (USD bn)	GDP dev. (%)
S1 CPS	2030	230	85	260	37.4	1,449	591	245	956	2,161	+0	17.8	0.00
S1 CPS	2040	405	145	330	43.6	1,949	534	253	980	2,220	+0	15.1	0.00
S1 CPS	2050	550	200	360	45.4	2,506	517	237	972	2,176	+0	12.4	0.00
S2 APS	2030	296	99	255	42.4	1,331	543	436	889	2,386	+224	34.0	0.33
S2 APS	2040	657	207	275	57.7	1,452	398	515	739	2,257	+37	35.3	0.33
S2 APS	2050	1,025	324	230	66.3	1,536	317	508	584	1,966	-210	29.7	0.31
S3 AJGT	2030	330	109	240	44.8	1,273	520	618	839	2,623	+462	46.4	0.54
S3 AJGT	2040	894	254	195	70.4	1,010	277	810	542	2,433	+214	53.6	0.66
S3 AJGT	2050	1,452	390	120	83.1	752	155	780	314	1,969	-206	42.5	0.54

*Total energy-sector jobs include direct, indirect and induced employment. Net vs S1 compares total energy-sector jobs. GDP deviation is relative to S1 baseline GDP.

4.2. Gross and net employment

The employment direct by segment is displayed in Fig. 4 and Table 6. There are currently approximately 0.38 million direct green full-time equivalents (FTE) in the energy sector and 0.90 million direct coal-value chain workers, including 0.32 million

formal miners and 0.48 million informal workers. S3 also shows that direct green jobs will increase to 0.62 million in 2030 and 0.81 million in 2040, with the installation of rooftop and distributed solar energy (0.25 million green jobs in 2030) and O&M (0.36 million green jobs in 2050) driving growth. In S3, coal value-chain employment declines to 0.31 million jobs by 2050, while in S1 it stands at 0.97 million jobs – driven by increases in coal output, which outweigh gains in labour productivity.

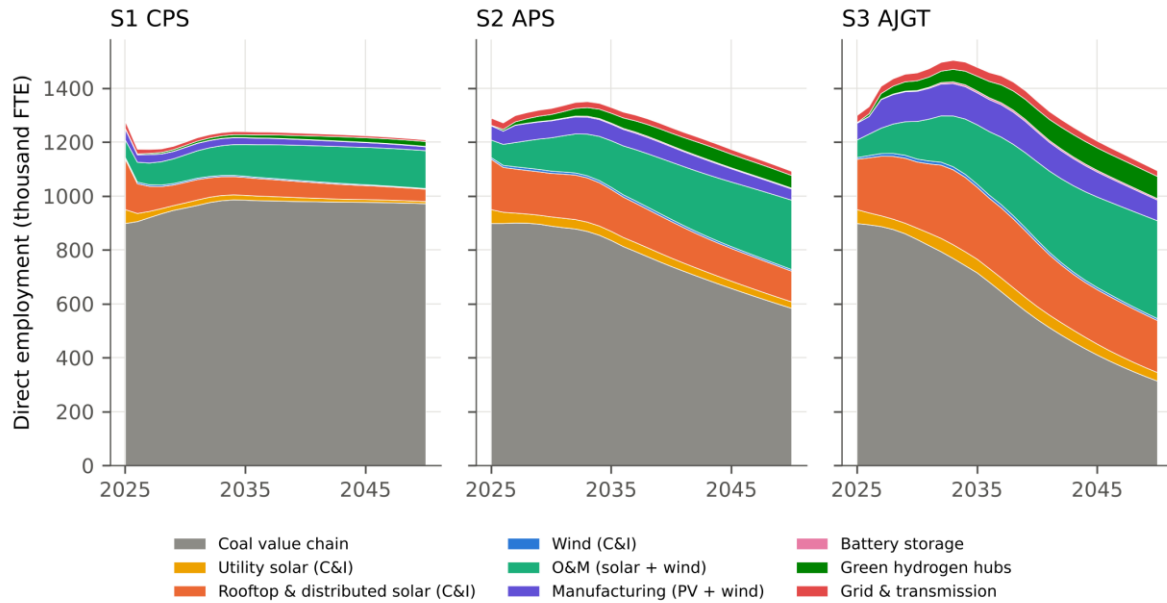


Fig. 4. Direct employment by segment and scenario, 2025–2050. Grey shows the coal value chain (formal and informal mining, plant O&M and construction); coloured segments are green-economy activities.

Table 6. Direct employment by segment, scenario and year (thousand FTE).

Segment	S1 2030	S1 2040	S1 2050	S2 2030	S2 2040	S2 2050	S3 2030	S3 2040	S3 2050
Utility solar (C&I)	19.0	13.8	8.2	34.1	31.3	24.0	42.1	48.0	31.7
Rooftop & distributed solar (C&I)	76.1	58.8	45.7	161.4	135.5	113.8	245.5	236.0	193.0
Wind (C&I)	5.4	4.1	2.4	8.4	8.1	6.2	10.8	10.3	7.2
O&M (solar + wind)	96.7	131.5	140.5	123.7	212.2	257.5	139.6	290.5	363.2
Manufacturing (PV + wind)	27.3	21.0	14.5	63.1	57.0	41.4	111.9	111.3	76.6
Battery storage	0.8	1.3	1.5	1.8	4.1	3.1	2.8	7.1	5.4
Green hydrogen hubs	6.7	13.6	18.0	21.6	46.6	47.0	36.2	76.0	82.2
Grid & transmission	12.4	9.1	5.8	22.4	20.1	15.4	29.2	30.6	21.0
Coal mining (formal)	332.6	347.6	351.4	308.3	261.7	211.5	296.3	192.8	114.0
Coal mining (informal)	498.9	521.4	527.1	462.4	392.5	317.3	444.4	289.2	171.0
Coal power (O&M + build)	124.8	110.9	93.5	118.2	84.6	55.0	98.6	60.0	28.7

Including indirect and induced effects, total energy-sector employment in S3 exceeds S1 by 462,000 jobs in 2030 and 214,000 in 2040, but falls 206,000 below S1 in 2050 (Table 5). The net dividend peaks at about 483,000 jobs in 2032 under S3 and 243,000 in 2028 under S2, and turns negative in 2045 and 2042, respectively. Summed over 2026–2050, S3 adds 5.61 million net job-years and S2 1.52 million. There is US\$1.22 trillion in cumulative green capital expenditures in S3 versus US\$0.84 trillion in S2 and US\$0.40 trillion in S1.

Table 7 shows the cause of the falling profile. Green technologies require significantly more of the workforce to construct per dollar of capital invested, with rooftop solar

generating 39.0 job-years per US\$1M, distributed solar 20.8 job-years per US\$1M and utility solar 7.2 job-years per US\$1M, compared to 2.5 job-years per US\$1M for coal power. In terms of Employment per TWh of electricity generated, by far the labour-intensive value chain is the coal operating value chain at approximately 612 FTE per TWh, followed by utility solar O&M (171 FTE per TWh) and wind (124 FTE per TWh), which are labour-intensive due to coal mining being predominantly informal. This employment advantage will then diminish as the shift goes from a building process into an operation process.

Table 7. Labour intensity of build and operation by technology (base-case parameters, 2025).

Technology	Build job-years	Capex (USD	Build job-years	Operating FTE
------------	-----------------	------------	-----------------	---------------

	per MW	M/MW)	per USD M	per TWh
Utility-scale solar PV	3.23	0.45	7.2	171
Rooftop solar PV	23.43	0.60	39.0	428
Distributed / agri-solar	11.43	0.55	20.8	381
Onshore wind	2.27	0.85	2.7	124
Coal power (incl. mining)	2.50	1.00	2.5	612

Build includes construction, installation and domestic manufacturing. Operating FTE per TWh for coal includes plant O&M and formal plus informal mining at a load factor of 0.64.

4.3. Uncertainty in net employment, GDP and emissions

The Monte Carlo results (Fig. 5, Fig. 6 and Table 8) validate the qualitative trend and provide a quantification of its strength. The 90% interval and the mean of cumulative net job-years for S3 are −2.40 to 15.96 million and 6.47 million, respectively, while that for S2 is 0.50 to 1.03 million. The probability of a

positive cumulative net job-years outcome is 0.88 for S3 and 0.73 for S2. The near-term dividend is very strong—the probability of a positive net employment is 0.997 in S3 and 0.976 in S2, while in 2050 it is 0.28 and 0.13. GDP and emission outcomes are much less uncertain: the 2040 GDP deviation is 0.66% (90% interval 0.54–0.80%) in S3 and 0.33% (0.28–0.40%) in S2, and cumulative CO₂ avoided is 21.2 Gt (19.2–23.1 Gt) and 11.6 Gt (10.5–12.6 Gt). Avoiding climate and air-pollution damage is valued, monetised, and on average amounts to US\$2.14 trillion in S3 (2026–2050).

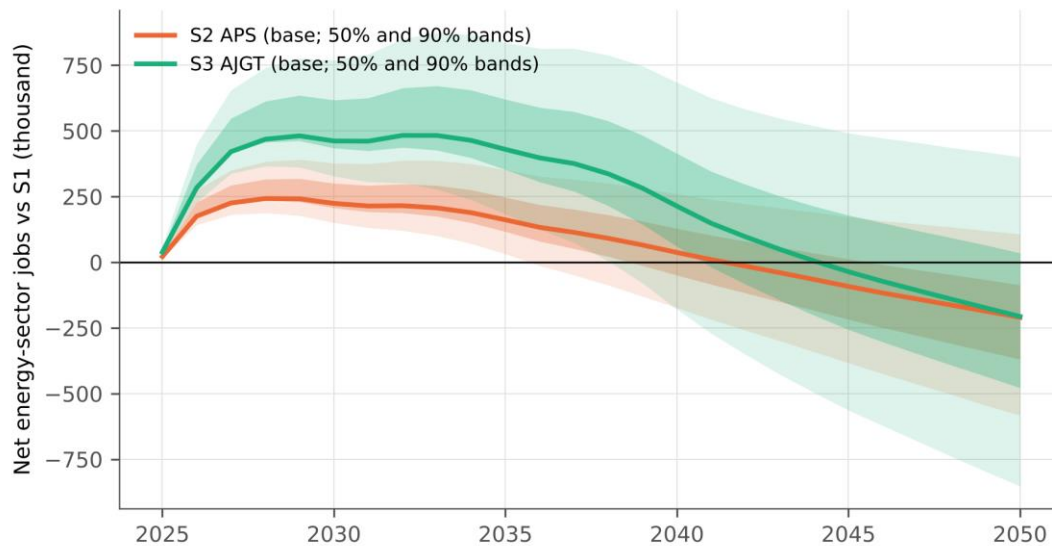


Fig. 5. Net energy-sector employment (direct, indirect and induced) of S2 and S3 relative to S1. Lines show the base case; shaded bands show the 50% and 90% Monte Carlo intervals ($n = 10,000$).

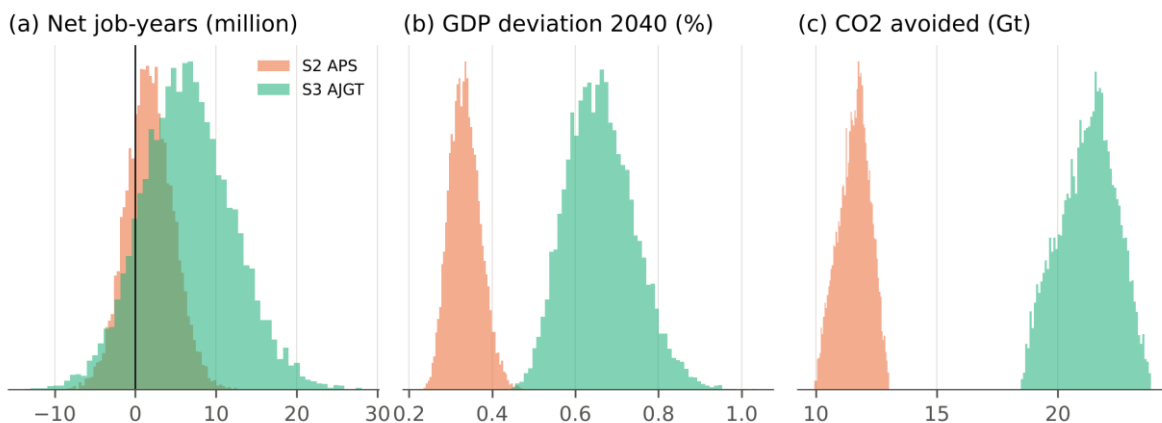


Fig. 6. Monte Carlo distributions of (a) cumulative net job-years 2026–2050, (b) GDP deviation in 2040 and (c) cumulative CO₂ avoided, relative to S1.

Table 8. Monte Carlo statistics for key outcomes relative to S1 (n = 10,000).

Scenario	Output (relative to S1)	Mean	SD	P5	Median	P95	Pr(>0)
S2 APS	Cumulative net job-years 2026-2050 (million)	1.75	2.91	-2.92	1.70	6.59	0.727
S2 APS	Net energy-sector jobs 2035 (thousand)	183.93	97.55	31.80	179.70	351.29	0.976
S2 APS	Net energy-sector jobs 2050 (thousand)	-231.17	210.41	-582.59	-225.79	107.14	0.131
S2 APS	GDP deviation 2040 (%)	0.33	0.04	0.28	0.33	0.40	1.000
S2 APS	Cumulative CO2 avoided 2026-2050 (Gt)	11.59	0.64	10.46	11.63	12.59	1.000
S2 APS	Avoided externality, cumulative (USD bn)	1,168.49	329.84	703.28	1,125.51	1,780.15	1.000
S3 AJGT	Cumulative net job-years 2026-2050 (million)	6.47	5.62	-2.40	6.29	15.96	0.881
S3 AJGT	Net energy-sector jobs 2035 (thousand)	491.29	199.37	183.51	480.03	836.03	0.997
S3 AJGT	Net energy-sector jobs 2050 (thousand)	-223.42	383.33	-852.00	-220.74	400.86	0.280
S3 AJGT	GDP deviation 2040 (%)	0.66	0.08	0.54	0.66	0.80	1.000
S3 AJGT	Cumulative CO2 avoided 2026-2050 (Gt)	21.23	1.15	19.22	21.31	23.06	1.000
S3 AJGT	Avoided externality, cumulative (USD bn)	2,140.58	604.03	1,287.88	2,062.20	3,260.33	1.000

4.4. Composition of green employment: phase, skill and gender

The composition of direct green employment can be seen in Fig. 7 and Table 9. The construction and installation share is largest until the late 2030s (0.41 million jobs in S3 in 2040), and then the O&M share is largest (0.36 million jobs in S3 in 2050), moving toward more long-lived and local job shares. Production reaches peak values around 0.11 million in S3 in

the 2030s, nearly twice as much as in S2 and four times the values in S1, due to increased localisation and exports. The share of green jobs across the three skill levels is approximately 48% semi-skilled, 26-27% high-skilled, and 25-27% low-skilled. If the percentage of green jobs among women is only 11% (CEEW and NRDC, 2026), only approximately 89,000 green jobs would be available to women in S3 by 2040.

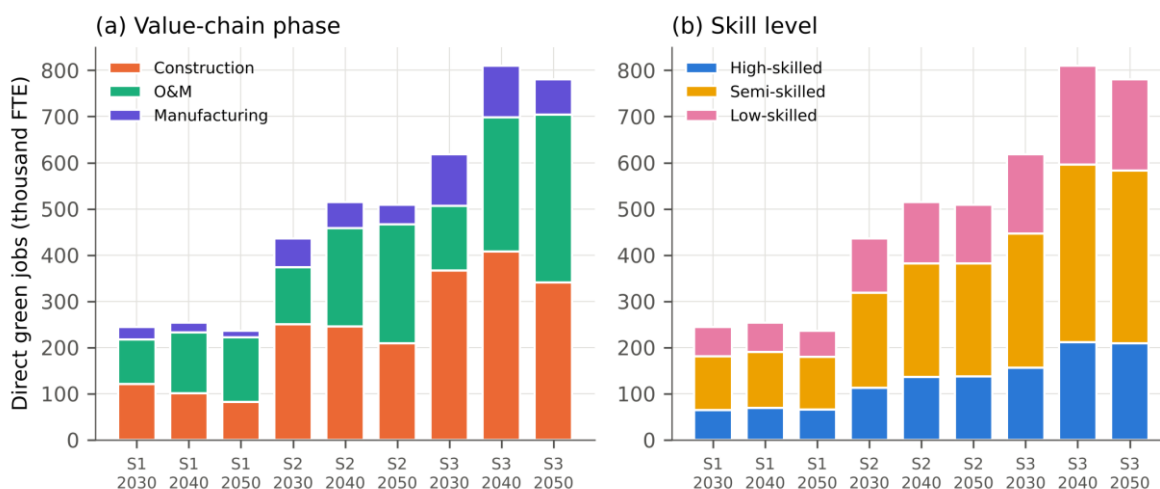
**Fig. 7.** Direct green employment by (a) value-chain phase and (b) skill level, by scenario and milestone year.

Table 9. Direct green employment by phase, skill level and gender (thousand FTE).

Scenario	Year	Construction & installation (k)	O&M (k)	Manufacturing (k)	High-skilled (k)	Semi-skilled (k)	Low-skilled (k)	Women (k)
S1 CPS	2030	120.5	96.7	27.3	64.6	116.2	63.7	26.9
S1 CPS	2040	100.7	131.5	21.0	68.8	121.6	62.8	27.9
S1 CPS	2050	81.6	140.5	14.5	65.4	114.2	56.9	26.0
S2 APS	2030	249.7	123.7	63.1	112.2	205.8	118.6	48.0
S2 APS	2040	245.7	212.2	57.0	136.5	245.2	133.3	56.6
S2 APS	2050	209.5	257.5	41.4	137.9	243.7	126.8	55.9
S3 AJGT	2030	366.7	139.6	111.9	155.9	290.7	171.5	68.0
S3 AJGT	2040	408.0	290.5	111.3	211.4	384.5	213.9	89.1
S3 AJGT	2050	340.5	363.2	76.6	209.4	373.1	197.8	85.8

4.5. Drivers of green employment: LMDI decomposition

LMDI results (Figure 8; Table 10) indicate that there are three forces. Over 2025–2050 in S3, direct green employment rises by 380,000 jobs. The increase in the scale of investment contributes 196,000 jobs, with every additional dollar spent on more labour-intensive technologies (solar, storage and hydrogen) contributing 395,000 jobs, whereas every additional dollar spent on less labour-intensive technologies (utility solar, storage and hydrogen) detracts 211,000 jobs. The intensity

effect is positive, as a declining capital cost boosts the number of jobs per dollar more than reducing jobs per megawatt, and a growing O&M workforce is not directly tied to investing in renewable energy. The proximate cause of the declining net dividend is the shift to minus in the scale effect in the final decade (2040-2050) with annual investment flat. In S1, the scale effect is negative the entire way, since the lower cost of units lowers the amount of units invested in a slowly growing deployment programme.

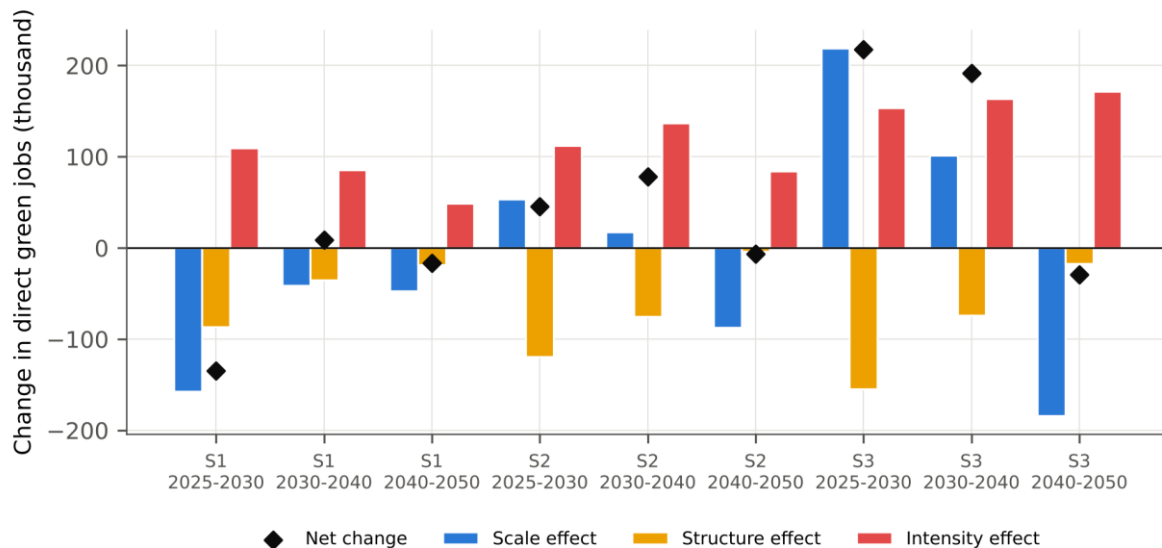


Fig. 8. LMDI decomposition of the change in direct green employment into scale, structure (technology mix) and intensity (jobs per dollar) effects by scenario and period.

Table 10. Additive LMDI decomposition of direct green employment (thousand FTE).

Scenario	Period	Initial jobs (k)	Scale effect (k)	Structure effect (k)	Intensity effect (k)	Final jobs (k)	Residual
S1 CPS	2025-2030	378.9	-157.5	-86.5	+109.6	244.5	≈0
S1 CPS	2030-2040	244.5	-41.3	-35.2	+85.3	253.3	≈0
S1 CPS	2040-2050	253.3	-47.0	-18.8	+49.1	236.6	≈0
S1 CPS	2025-2050	378.9	-258.1	-147.5	+263.3	236.6	≈0
S2 APS	2025-2030	390.9	+53.2	-119.5	+111.9	436.5	≈0

S2 APS	2030-2040	436.5	+17.3	-75.6	+136.8	515.0	≈ 0
S2 APS	2040-2050	515.0	-87.2	-3.6	+84.2	508.4	≈ 0
S2 APS	2025-2050	390.9	-1.7	-171.2	+290.3	508.4	≈ 0
S3 AJGT	2025-2030	400.5	+218.8	-154.9	+153.6	618.1	≈ 0
S3 AJGT	2030-2040	618.1	+101.6	-73.8	+163.9	809.8	≈ 0
S3 AJGT	2040-2050	809.8	-184.0	-17.0	+171.6	780.3	≈ 0
S3 AJGT	2025-2050	400.5	+195.6	-210.8	+395.1	780.3	≈ 0

4.6. Global sensitivity analysis

Cumulative net job-years are determined by only a few parameters, as confirmed by Sobol indices (Fig.9; Table 11), which show that there is no significant interaction effect (sum of first-order indices is 0.96). The green indirect and induced multiplier ($ST = 0.237$), the informal-to-formal coal workers ratio (0.183), and the rate at which employment factors decline (0.160) account for 58% of the variance, followed by the coal multiplier (0.127), the rooftop-solar installation factor (0.112)

and coal labour-productivity growth (0.081). Factors of employment are irrelevant to wind, storage and hydrogen. The outcome of the GDP is based on the investment multiplier (0.471), crowding-out (0.382) and deployment realisation (0.165). There thus seem to be three research priorities: obtaining improved estimates of the supply-chain multipliers, obtaining better estimates of the size of the informal coal mining workforce and of the rate at which labor requirements decline.

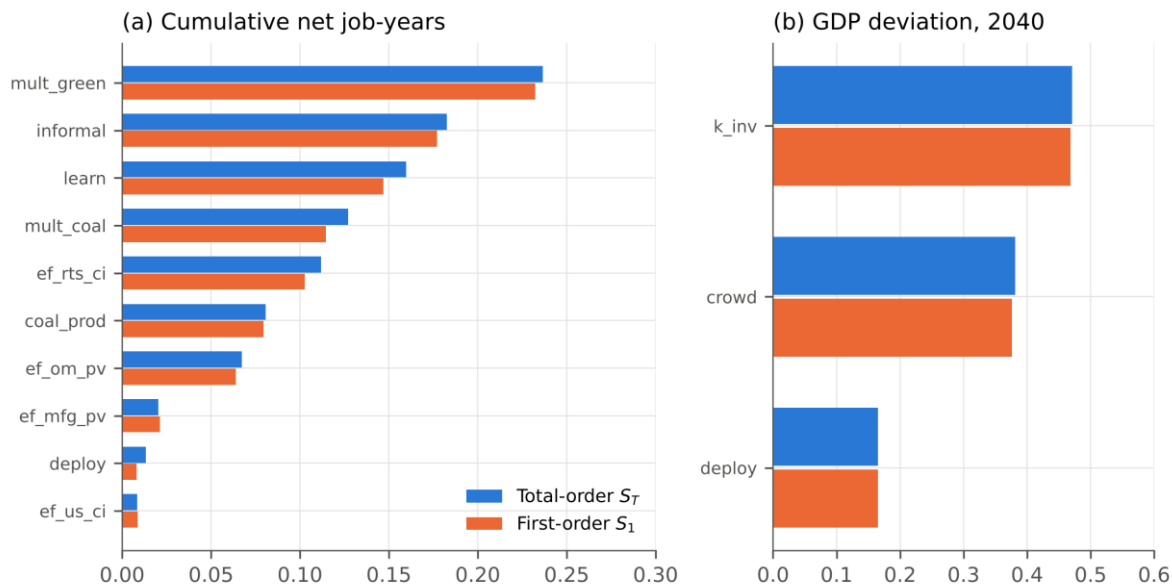


Fig. 9. First-order (S_1) and total-order (S_T) Sobol indices for (a) cumulative net job-years of S3 relative to S1 and (b) the 2040 GDP deviation (N = 8,192).

Table 11. Sobol sensitivity indices (parameters with $S_T > 0.005$ for either output).

Parameter	S_1 jobs ($\pm 95\%$ CI)	S_T jobs ($\pm 95\%$ CI)	S_1 GDP	S_T GDP
Indirect+induced multiplier, green	0.232 ± 0.014	0.237 ± 0.009	0.000	0.000
Informal-to-formal coal ratio	0.177 ± 0.014	0.183 ± 0.008	0.000	0.000
Employment-factor decline rate	0.147 ± 0.012	0.160 ± 0.006	0.000	0.000
Indirect+induced multiplier, coal	0.115 ± 0.011	0.127 ± 0.005	0.000	0.000
Rooftop solar C&I factor	0.103 ± 0.009	0.112 ± 0.004	0.000	0.000
Coal labour-productivity growth	0.079 ± 0.009	0.081 ± 0.003	0.000	0.000
Solar O&M factor (utility)	0.064 ± 0.008	0.067 ± 0.002	0.000	0.000
PV manufacturing factor	0.021 ± 0.004	0.020 ± 0.001	0.000	0.000
Deployment realisation factor	0.008 ± 0.004	0.013 ± 0.001	0.165	0.165
Utility solar C&I factor	0.009 ± 0.003	0.009 ± 0.000	0.000	0.000
Distributed/agri-solar C&I factor	0.004 ± 0.002	0.006 ± 0.000	0.000	0.000

Investment multiplier	0.000 ± 0.000	0.000 ± 0.000	0.469	0.471
Crowding-out share	0.000 ± 0.000	0.000 ± 0.000	0.376	0.382

4.7. Regional mismatch and just-transition burden

Fig. 10 and Table 12 allocate the S3–S1 differences in direct employment to states. The mismatch is stark. Odisha (−154,000 in 2050), Chhattisgarh (−135,000), Jharkhand (−124,000), Madhya Pradesh (−79,000), Telangana (−35,000) and West Bengal (−27,000) together lose about 553,000 direct jobs relative to S1 by 2050, with losses already visible by 2035.

Gains concentrate in Gujarat (+144,000), Rajasthan (+115,000), Maharashtra (+68,000), Karnataka and Tamil Nadu, the states that account for most current solar and wind additions and manufacturing. Under current siting patterns, Odisha, Chhattisgarh and Jharkhand together receive only about 1.5% of green C&I and O&M employment.

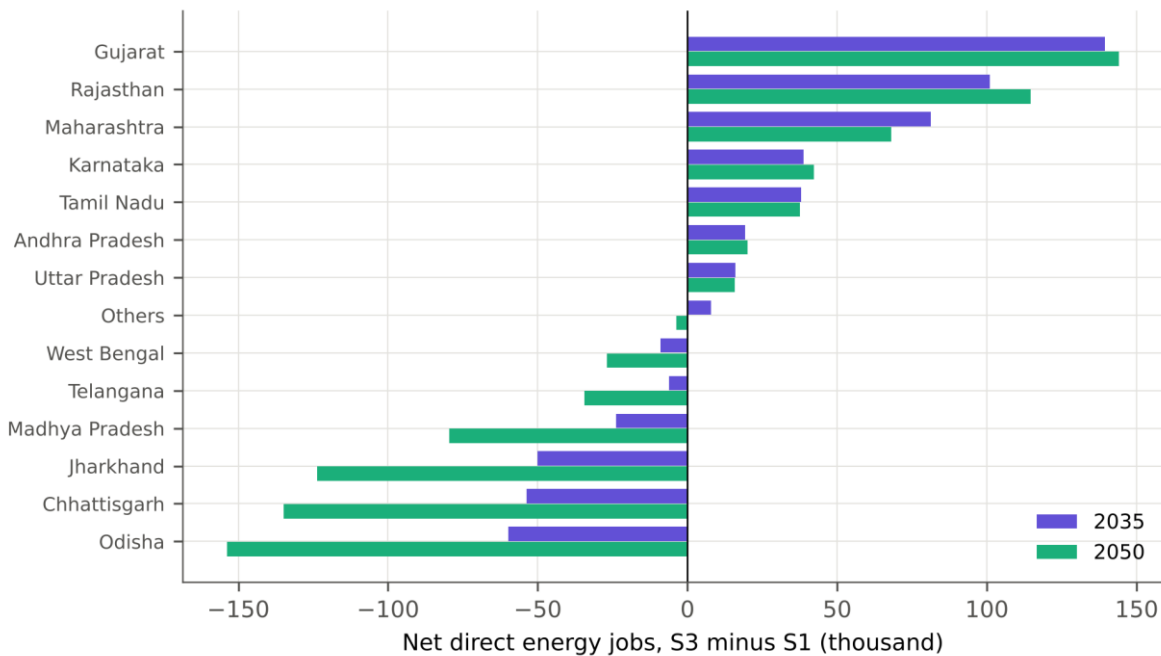


Fig. 10. Net change in direct energy-sector employment by state, S3 relative to S1, in 2035 and 2050.

Table 12. State-level distribution of direct employment change, S3 relative to S1 (thousand FTE).

State	Coal-production share	Green gain 2035 (k)	Coal loss 2035 (k)	Net 2035 (k)	Green gain 2050 (k)	Coal loss 2050 (k)	Net 2050 (k)
Odisha	0.240	4.9	-64.8	-59.9	4.3	-158.0	-153.7
Chhattisgarh	0.210	2.9	-56.7	-53.8	3.4	-138.2	-134.9
Jharkhand	0.190	1.2	-51.3	-50.0	1.4	-125.1	-123.6
Madhya Pradesh	0.150	16.6	-40.5	-23.9	19.3	-98.7	-79.5
Telangana	0.070	12.8	-18.9	-6.1	11.6	-46.1	-34.5
West Bengal	0.045	3.1	-12.1	-9.0	2.7	-29.6	-26.9
Maharashtra	0.065	98.8	-17.5	+81.2	110.9	-42.8	+68.1
Gujarat	0.000	139.4	-0.0	+139.4	144.0	-0.0	+144.0
Rajasthan	0.000	101.0	-0.0	+101.0	114.5	-0.0	+114.5
Karnataka	0.000	38.8	-0.0	+38.8	42.3	-0.0	+42.3
Tamil Nadu	0.000	38.0	-0.0	+38.0	37.6	-0.0	+37.6
Andhra Pradesh	0.000	19.2	-0.0	+19.2	20.0	-0.0	+20.0
Uttar Pradesh	0.000	16.0	-0.0	+16.0	15.8	-0.0	+15.8
Others	0.030	15.9	-8.1	+7.8	16.1	-19.7	-3.6

Coal losses are allocated by approximate 2023–24 production

shares; green C&I and O&M by 2025 capacity-addition shares;

manufacturing by announced manufacturing locations. Allocation keys are held constant, so the table shows the mismatch implied by current siting patterns.

The aggregate transition burden is, however, manageable if it is planned (Table 13). Under S2, the decline in coal employment never exceeds natural attrition, so no worker is displaced beyond retirements. Under S3, about 237,000 workers are

displaced beyond attrition over 2025–2050; with active re-absorption, the transition-unemployment pool peaks at about 40,000 in 2039 and amounts to some 0.5 million person-years. A reskilling budget of US\$3,000 per displaced worker would cost about US\$0.7 billion in total, less than 0.1% of cumulative green investment in S3.

Table 13. Just-transition indicators for coal-sector workers.

Scenario	Cumulative displaced workers (k)	Peak transition pool (k)	Peak year	Transition person-years (k)	Reskilling budget (USD bn) [†]
S1 CPS	0.0	0.0	–	0.0	0.00
S2 APS	0.0	0.0	–	0.0	0.00
S3 AJGT	237.0	40.3	2039	500.8	0.71

Displacement is the decline in coal value-chain employment in excess of 2.5% annual attrition. [†]At US\$3,000 per displaced worker.

4.8. Macroeconomic effects and decoupling

GDP is higher in both green scenarios throughout the horizon (Table 5): by 0.33% in 2030 and 0.31% in 2050 in S2, and by 0.54%, 0.66% and 0.54% in 2030, 2040 and 2050 in S3. There are investment-driven early gains followed by increasing import costs and coal fuel cost-avoidance gains. The import cost of coal in 2050 is US – 8.2 billion (in S3) compared to US – 25.2 billion (in S1). The pattern of decoupling is shown in

Fig. 11. When CO₂ in S1 is doubled, the increase is relatively small compared to GDP, which is quadrupled. The emissions level in S2 levels off around the mid-2030s at around 1.5 Gt. Absolute decoupling is achieved (only in S3), with emissions reaching a maximum around 2030 and declining by 38% (by 2050) compared to the level in 2025. In each of the three scenarios, employment in the energy sector is lower at the end of the period of 2025 than at the outset, indicating that a world of green energy can have both higher productivity and lower energy employment, but that employment growth will have to occur in other activities.

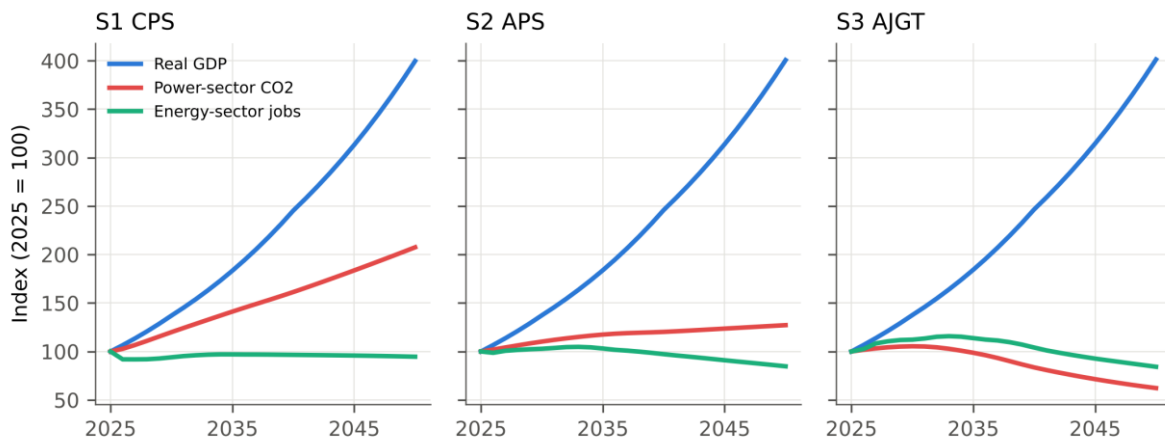


Fig. 11. Decoupling of real GDP, power-sector CO₂ and energy-sector employment, indexed to 2025 = 100, by scenario.

4.9. Composite sustainability ranking

The highest value of entropy weight corresponds to GDP deviation (0.285), while CO₂ intensity (0.204) and clean generation share (0.202) are next, followed by employment (0.159), import bill (0.080) and transition unemployment (0.071) (Table 14). The resulting GSI (Fig. 12, Table 15) increases in all scenarios, until reaching a plateau from the mid-2030s onwards. In 2050 S3 scores 0.750, S2 0.507 and S1

0.189. TOPSIS yields the same order, and the closeness coefficients are 0.799, 0.593, and 0.201. The heat map in Fig. 12b highlights the opposites contained in this ranking: S3 is the most successful in terms of GDP, emissions, clean share and import dependence, whereas the least successful in terms of transition unemployment and energy-sector employment, the latter being achieved most of all by S1, which maintains a high employment level for the coal mining industry until 2050.

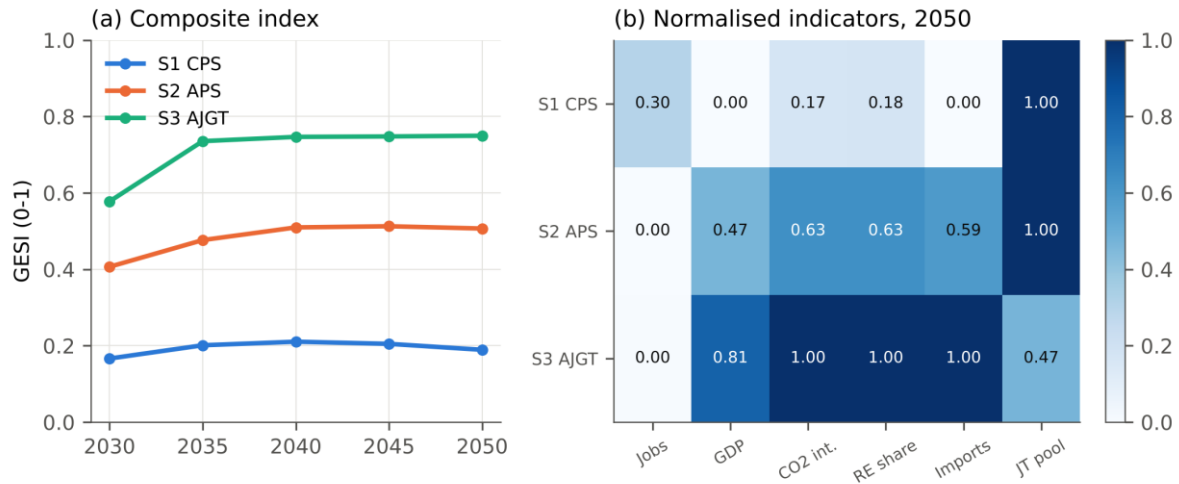


Fig. 12. (a) Entropy-weighted Green Economy Sustainability Index (GESI) by scenario and year; (b) normalised indicator scores in 2050 (1 = best performance among the 15 scenario-year alternatives).

Table 14. Indicators, entropy and objective weights of the GESI.

Indicator	Definition	Direction	Entropy e_j	Weight w_j
Employment	Total energy-sector employment incl. indirect (million)	+	0.907	0.159
GDP	GDP deviation from S1 (%)	+	0.833	0.285
Intensity	Power-sector CO ₂ intensity (g/kWh)	-	0.880	0.204
RE share	Clean share of electricity generation (%)	+	0.881	0.202
Import bill	Thermal-coal import bill (USD bn)	-	0.953	0.080
JT pool	Transition unemployment pool (thousand)	-	0.958	0.071

Table 15. GESI scores (2030–2050) and TOPSIS ranking of scenarios in 2050.

Scenario	GESI 2030	GESI 2035	GESI 2040	GESI 2045	GESI 2050	TOPSIS D^+	TOPSIS D^-	Closeness C_i	Rank
S1 CPS	0.166	0.201	0.211	0.205	0.189	0.284	0.071	0.201	3
S2 APS	0.407	0.476	0.510	0.513	0.507	0.122	0.178	0.593	2
S3 AJGT	0.578	0.735	0.747	0.748	0.750	0.071	0.284	0.799	1

5. Discussion

5.1. Interpretation and comparison with previous studies

Results are in favour of H1 in a probabilistic sense, as increasing the speed of the green transition increases the likelihood of an increase in employment in the energy sector in India by approximately 88%. These estimates are in line with the global result of an increased number of energy jobs due to ambitious climate policy, as suggested by Pais et al. (2021), as well as the positive but low magnitudes found by input–output or macro-econometric studies for Europe and the United States (Lehr et al., 2012; Markandya et al., 2016; Garrett-Peltier, 2017). This lower estimate of the gross green workforce (0.6–0.8 million annual FTE in S3 in the 2030s) than the number of job-years in India's projections to 2030 reported by CEEW and NRDC (2026) is a result of (i) the focus on annual full-time equivalent occupations in this analysis, rather than accumulated

job-years; (ii) the exclusion of bioenergy, hydropower and wider efficiency and electric-mobility occupations; and (iii) the incorporation of learning decay. The differences are definitional (and not mutually exclusive), and it is important to report whether it's jobs in a year or job-years in a programme.

There is a pronounced trend in favor of H2, which is the key new discovery. The net dividend is very much skewed towards the early years, being large and virtually guaranteed in the 2030s and lost in the 2040s. This is done by two mechanisms. First, the mix of labour in the coal mining/coal burning operation and the labour in the solar and wind operation differ – to run the solar and wind, fewer workers are required per unit of energy supplied than are required with coal mining that uses informal labour. Second, the automation and scale economies associated with the disaggregation of employment factors implied by global data (IRENA and ILO, 2025) slowly bring

down the amount of required labour; the third source of uncertainty is the learning rate. This is not an argument against transition but in favour of the local context of transition for everyone. The reduction in the amount of labour used per unit of energy (a productivity gain) in a well-functioning economy allows workers and incomes to be redeployed in other sectors, and GDP is increased across the board because of the transition. What it does imply, however, is that no longer can an energy sector job boom last for eight years or more, providing a 'safe haven' for jobs, and no longer can labour-market policy even look to an ad hoc job push in this sector. The five times higher employment per dollar of rooftop and distributed solar power compared to utility-scale solar and almost 15 times more than coal power is supported (c.f. CEEW and NRDC 2017; 2026). As the rooftop installation factor is ranked 5th among the Sobol analysis, the policy mix between distributed and utility-scale solar is one of the few factors directly controlled by policies that can impact employment. This support for H4 is reinforced because losses felt at the national level are concentrated in six states in the eastern and central part of the country; a region characterised by poverty, whilst benefits are gained in more industrial states to the west and south of India, mirroring the results of Jakob et al. (2020). This is not because the solar resource corresponds to coal districts is good (Pai et al., 2020), but is a siting choice. Supporting the use of H5, GDP is 0.3-0.7% higher, there is a

significant decline in emissions, and both GDP methods have the same first rank using the GESI and TOPSIS approach, with all the rankings being robust.

5.2. Policy implications

The results are converted into the policy matrix shown in Table 16. There are four main priorities. First, policy should make the most of the 'build phase' growth spurt by targeting distributed solar power – this can deliver the maximum employment for every rupee invested, and jobs can be located throughout cities, towns and farms. Second, localisation and 25 G Watt exports of modules bring up the manufacturing employment levels in S3 to approximately 110,000 in the 2030s, so the dividend needs to be extended beyond build-out to manufacturing and exports. Third, Just-transition policy should also be 'place-based': if a just transition' is to take place, it should have an impact – steering a fraction of solar and storage and manufacturing capacity to coal regions, making use of coal land and grid connections, will transform a coal region into a measure of replacement. Fourth, the transition burden on workers is not too large; it is estimated that the reskilling budget is around US\$0.7 billion, which is not a significant impediment to green investing—rather, the issue is institutional capacity. There is also a need to increase women's participation through affirmative action, as 11% participation will leave most of the new green jobs to the male population.

Table 16. Policy matrix linking model findings to instruments.

Finding	Mechanism in model	Policy instrument	Expected effect
Dividend is front-loaded	Build-to-operate shift; learning decay	Sequence deployment to smooth investment; continuous pipeline of tenders	Lengthens high-employment phase
Distributed solar most job-intensive	e ^{CI} rooftop >> utility	Expand PM Surya Ghar and PM-KUSUM; low-cost finance for small installers	Higher jobs per rupee; dispersed employment
Manufacturing sustains jobs	Localisation δ and exports X	Production-linked incentives across cell, wafer and polysilicon; export credit	Durable industrial employment
Losses concentrated in coal states	Production-share allocation	Siting quotas or premiums for RE and manufacturing in coal districts; repurpose mine land	Reduces regional mismatch
Informal coal work drives uncertainty	ω ratio	Register informal workers; extend social protection	Visible, targeted support
Transition burden affordable	Labour pool U, rate r	Dedicated just-transition fund; reskilling linked to placements	Shorter unemployment spells
Low female participation	11% female share	Gender targets in skilling programmes and tenders	More inclusive green workforce

5.3. Limitations and future research

There are some qualifications to the results. By first, the model

is only considering power, storage, transmission and green hydrogen; in many other sectors, such as energy efficiency,

electric mobility and green buildings, as well as bioenergy and the circular economy, employment creation is much higher, making this figure potentially underestimate the job creation potential for the green economy as a whole. Second, indirect and induced impacts rely on aggregate multipliers instead of a full input–output table: based on the results of the Sobol analysis, these multipliers are important, and a regionalised input–output table is a priority. Third, the macro module is an accounting system, and as such is not considered a price feedback, labour-supply constraint, or a wage effect, so the GDP results should be viewed as indicative orders of magnitude. Finally, fourth, all regionally allocated capacity is fixed key capacity, and the possibility of new siting policies is not captured endogenously. Fifth, informal employment in the coal sector is hard to measure, and the reasonable range of 1-3 informal workers per formal worker is a significant factor of uncertainty. Finally, the results can be considered model outputs based on given conditions and hence do not represent forecasts. Future research should attempt to link GEMSIM-IN with district-level resource and labour data, and an input–output table for India, and test the robustness of the identified time profile.

6. Conclusions

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