Supplementary information

Technology modularity shapes latecomer cost convergence in renewables

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Supplementary Notes

Note S1: Overview of SCALE (Stage-Cost Assessment of Learning and Experience)

We developed the Stage-Cost Assessment of Learning and Experience (SCALE) model to project the path-dependent installed costs of utility-scale solar PV and onshore wind through 2050 (Fig. S1). The model integrates six steps: three bottom-up steps (a harmonized cost panel, take-off year detection, and the C-SPDM, Cost-coupled Stage-Pathway Diffusion Model) to build the empirical foundation; two forward-looking steps (Wright's-law estimation and Monte Carlo projection) to forecast trajectories; and a counterfactual steps to quantify the impacts of targeted policy interventions for Laggard countries.

(1) Step 1: Data harmonization

The Data Harmonization Step addresses sparse coverage in IRENA installed-cost records, which span 45 countries for utility-scale solar PV and onshore wind. Random Forest (RF) model imputes log-transformed costs from cumulative national capacity, global component prices, resource potential (PVOUT, wind power density), GDP and demographic covariates. Ten-fold cross-validation yields R^2 of 0.878 (RMSE =0.202) for solar PV and 0.63 (RMSE =0.145) for onshore wind on the log-cost target (Fig. S2). Applying the fitted models to country-year combinations with complete predictor coverage extended empirical reach to 168 countries for solar PV and 164 for onshore wind, yielding a harmonised installed-cost panel for every country and year required by the downstream plant-level analyses.

(2) Step 2: Take-off detection

We reconciled take-off years through a three-stage framework combining statistical detection with documentary verification. FOBI, our primary benchmark, locates the earliest statistically significant change point via piece-wise Bayesian regression, avoiding arbitrary penetration cut-offs[1]. A supplementary cascade-gated model covers countries outside the FOBI sample and flags disagreements, applying the Bai-Perron structural-break test to log-penetration series stratified by grid size (Small <20 GW, Medium 20–100 GW, Large >100 GW). Technology-specific thresholds reflect distinct deployment dynamics, with solar PV floors set at 1.0–3.5% and wind floors at 1.0–2.0%, while required compound annual growth rates rise from 15% for wind to 20% for solar PV in larger grids. Countries adopt the FOBI year when the two methods agree within ±2 years or when only FOBI detects a take-off. Divergences greater than two years or cascade-only detections trigger historical calibration, which is especially common in step-function markets where negligible pre-commissioning capacity fails FOBI's formative-phase threshold and the cascade year captures an abrupt commissioning marker rather than a trajectory shift. Sensitivity tests across Relaxed and Strict threshold scenarios preserved 94.0–97.0% of take-off years within ±2 years of the Base assignment and constrained count fluctuations to ≤25%, confirming the framework's robustness (Table S1).

Historical calibration assigns the take-off year to the first calendar year satisfying three conditions simultaneously: the enabling policy instrument must be operational rather than merely legislated, the first commercial-scale projects must reach commissioning, and annual additions must enter sustained multi-year expansion documented in national grid reports or international databases. This exogenous evidentiary basis breaks the circularity that would otherwise arise from threshold adjustments applied to the same growth data driving FOBI and the cascade-gated model. For solar PV, 24 countries required calibration (Tables S2, S3), with Germany, Spain, Belgium, Portugal, Austria, and Greece uniformly adjusted to 2010 under the baseline rule and the remaining 18 nations spanning 2011–2017. This distribution traces global solar diffusion from early followers such as Ukraine (2011) and Romania (2012) to a late-2010s cohort concentrated around El Salvador, Hungary, the UAE, and Vietnam (all 2017). For onshore wind, 9 countries underwent calibration (Tables S4, S5). Denmark, with formative activity dating to 1991, was adjusted to 2000 under the baseline rule, while the remaining 8 calibrated years (2004–2014) capture sequential expansion from early adopters such as New Zealand (2004), Ireland (2006), and Estonia (2007) to Central American entrants including Honduras (2011), Costa Rica (2014), and Panama (2014).

(3) Step 3: C-SPDM (core engine)

We assigned every country-year observation to one of six deployment stages through a priority-ordered rule cascade applied to four indicators: annual new capacity (two log-scale classes), installation cost (three classes), cumulative capacity (three log-scale classes), and penetration (three classes) (Table. S6). Log-transformation of capacity metrics prevented high-deployment outliers from dominating break optimisation. The cascade evaluated Mature Penetration, Accelerating Growth, Policy-Driven Scaling, Cost Parity, Formative Phase, and Early Adoption in priority order, ensuring that scale and penetration criteria override cost-based categories and preventing established deployers from being misclassified as nascent during transient cost fluctuations.

National trajectories were then compressed through run-length encoding and matched against ordered regular expressions identifying four pathways: Front-Runners entering Accelerating Growth or Mature Penetration before the technology-specific pioneer cutoff

(2010 for both solar PV and onshore wind); Gradualists reaching those stages without passing through Policy-Driven Scaling or Cost Parity; Leapfroggers entering directly at Accelerating Growth or Mature Penetration after the cutoff, or traversing Cost Parity before stabilising; and Laggards reaching Cost Parity without sustaining acceleration. Residual unmatched countries were diagnosed as stuck in early stages, policy collapses, or data-sparse trajectories, with Paths B and C collapsing into 'Late Movers' for onshore wind. We validated the C-SPDM stage assignments through unsupervised k-means clustering on country-year SHAP values extracted from the RF cost-imputation model, which yielded three robust clusters for both technologies with strong statistical concordance confirmed by Pearson chi-square residuals (Figs. S14–17).

(4) Step 4: Learning rate estimation

The Learning Rate Estimation Step fits Wright's law at the country level, as well as across specific pathway and deployment stage categories, extracting experience elasticities directly from the regression slope of log-cost on log-cumulative-capacity. Summary statistics computed across countries within each stage and pathway characterise the global distribution of learning rates and test whether the experience elasticity differs systematically between solar PV and onshore wind across their respective deployment regimes, providing the central parameter set for projection (Fig. 4; Note S5, Fig. S34).

(5) Step 5: Probabilistic cost projection

The Probabilistic Cost Projection Step simulates 100 Monte Carlo trajectories per country to 2050. Each trajectory updates capacity using pathway-stage-specific median growth and penetration rates, then evolves cost through the corresponding learning rate. Three hierarchical fallbacks ensure parameter coverage in sparsely populated cells, and technology-specific bounds floor learning at 2% (onshore wind) or 5% (solar PV) and cap it at 30% or 35% respectively, or the cell-specific 75th percentile when higher (Table S7). Stage transitions during the projection horizon discretely update growth and learning parameters, embedding C-SPDM regime shifts directly into the cost trajectory.

(6) Step 6: Counterfactual policy simulation

The Counterfactual Policy Step isolates intervention leverage for Laggard countries by perturbing growth rates, learning rates, or both to the 75th-percentile benchmark of successful pathways. Five scenarios, including Business-as-Usual, Leapfrog Learning (or Late-Mover Emulation for onshore wind), Accelerated Deployment, Technology Transfer, and Combined Policy, quantify the marginal cost reduction attributable to each policy lever. Variance decomposition closes the framework by partitioning 2023-2050 cross-country cost dispersion into country-attributable, pathway-attributable, stage-attributable, and joint components, identifying which structural feature dominates national cost outcomes (Figs. S38-41).

Note S2: Random Forest (RF) Model

Given the complex, non-linear relationships and potential variable interactions among technological progress, macroeconomic factors, and energy costs, this study employs a RF regression approach for modeling. RF is an ensemble learning method based on decision trees[2]. By integrating bootstrap sampling and random feature selection, it constructs a multitude of independent decision trees and aggregates their predictions via averaging. This mechanism effectively mitigates the high variance inherent in single decision trees, thereby substantially enhancing the model's generalization capability and robustness.

(1) Model training and hyperparameter tuning

RF models were fitted in the mlr3 framework using the ranger backend with 1000 trees, permutation-based variable importance, and a fixed seed (1234) for reproducibility[3-5]. To prevent overfitting and optimize model performance, we performed hyperparameter tuning for two key parameters: the number of variables randomly sampled as candidates at each split (mtry, ranged from 2 to 7) and the minimum number of observations in a terminal node (min.node.size, ranged from 5 to 25).

The optimal hyperparameters were determined using a random search algorithm restricted to 20 evaluations. During the tuning phase, model performance was evaluated by maximizing the R-squared metric via 5-fold cross-validation. Once the optimal hyperparameters were identified, the final model performance was assessed using a 10-fold cross-validation strategy.

(2) Model interpretation and variable importance

Traditional machine learning models are frequently characterized as 'black boxes'[6]. To alleviate this limitation, we employed SHapley Additive exPlanations (SHAP) to enhance the transparency and interpretability of our cost prediction model[7]. SHAP employs coalitional game theory to allocate the model's total predictive payoff among the input features. The marginal contribution of a specific feature j, is derived by evaluating the difference in model predictions when the feature is included versus when it is excluded. For each specific sample x_i, the predicted value $f(x_i)$ can be decomposed as follows:

$$f(x_i) = \emptyset_0(f, x) + \sum_{j=1}^{k} \emptyset_j(f, x_i) \tag{1}$$

where $\emptyset_0$ represents the expected baseline value of the model output, $\emptyset_j(f, x_i)$ denotes the specific impact of variable j on the prediction for sample x_i (i.e., the SHAP value), and k represents the total number of predictor variables.

To compute these values efficiently while maintaining robust approximations, we specifically employed the Kernel SHAP algorithm. Kernel SHAP is a model-agnostic approach that estimates the Shapley values by building a weighted linear surrogate model, utilizing a background dataset to represent the expected baseline predictions[7]. Kernel SHAP was applied to compute the marginal contribution of each feature to the predicted log-transformed cost. A background dataset comprising 150 randomly sampled observations was established. The global feature importance and directional impacts for the Solar PV and onshore wind model are presented in Figs. S3 and S4.

For solar PV, the global PV module price and deployment year jointly dominate predictive importance. Population and cumulative capacity demonstrate moderate predictive value, while socioeconomic and resource covariates contribute an order of magnitude less. Similarly, for onshore wind, deployment year and global turbine price remain the primary predictors. Cumulative capacity maintains a moderate predictive role, whereas the contributions of socioeconomic and resource covariates remain an order of magnitude lower. This association supports the learning curve theory[8], highlighting that global technology maturation and localized deployment scale are the primary indicators of cost reductions.

(3) SHAP dependence and interactions

Based on Kernel SHAP, we generated SHAP dependence plots to characterize the non-linear marginal effects and potential thresholds of individual input variables on the model's output (Fig. S5). Furthermore, to explicitly quantify the synergistic relationships between specific variable combinations (e.g., cumulative capacity and deployment year), we use the TreeSHAP algorithm to compute SHAP interaction values, employing the internal structural paths of tree-based ensembles to compute exact Shapley values and interaction indices efficiently[9]. Based on the Shapley interaction index from game theory, TreeSHAP decomposes the total SHAP value of a feature into the sum of its interaction effects with all other features (Fig. S6).

Fig. S5 shows that both calendar year and cumulative deployed capacity exert negative, monotonic contributions to solar PV installation costs, whereas onshore wind installation costs show a delayed transition from positive to negative SHAP contributions after 2015. This reflects the divergence in the installed cost dynamics between solar PV and onshore wind.

Through SHAP interaction analysis, the cumulative capacity and deployment year interaction emerged as the dominant pairwise effect, capturing how experience accumulation modulates the temporal cost-decline trajectory (Fig. S6). Specifically, country-years were split at the median capacity into Low-Capacity and High-Capacity groups, and a generalized additive model with group-specific smooth terms quantified the differential time-interaction effect. For solar PV, a highly modular technology with strong global learning spillovers, low-capacity countries reap significant 'leapfrogging dividends', evidenced by negative interaction values that accelerate cost reductions. Conversely, high-capacity countries increasingly encounter soft-cost bottlenecks, yielding positive interaction values that attenuate further cost declines. Conversely, onshore wind relies on localized infrastructure. High-capacity countries employ scale to reduce costs (negative interaction), whereas infrastructural barriers stagnate costs in low-capacity countries (positive interaction). This validates our path-dependent framework, requiring technology-specific policies: Leapfrog Learning for solar PV and Technology Transfer for onshore wind.

(4) SHAP-based k-means cluster analysis

While global SHAP importance reveals the overall impact of features, it may obscure underlying spatial or temporal heterogeneities. To identify distinct groups of observations driven by similar cost-reduction mechanisms, we applied K-means clustering directly to the SHAP value matrix. Compared to traditional clustering based on raw feature values, clustering in the SHAP explanation space offers two main advantages. First, it transitions the analysis from descriptive similarity (what the absolute values are) to mechanistic similarity (how the variables interact to drive predictions). Second, because SHAP values are derived directly from the trained RF model, this approach inherently captures complex non-linear dynamics and synergistic effects that traditional Euclidean distance metrics would ignore. Consequently, it enables the categorization of observations based on their shared predictive patterns of cost evolution rather than superficial characteristics.

The observations were partitioned into three distinct clusters. To ensure robust algorithmic convergence and avoid local optima, the K-means algorithm was executed using 25 random initial configurations (nstart =25). To elucidate the distinct predictive profiles of each subgroup, we constructed cluster representations by aggregating the mean SHAP values of each feature within the respective clusters. This approach established a hierarchy of absolute feature contributions (Figs. S7-9).

For solar PV (Fig. S8), the SHAP-defined clusters are delineated primarily by deployment year and global module price. These two temporal-technological variables account for the largest between-cluster variations in predictive contributions to installation costs. In contrast, socioeconomic and solar resource features exhibit comparable distributions across all clusters, indicating a marginal role in distinguishing cost regimes. Conversely, for onshore wind (Fig. S9), the clusters separate not only along turbine price and deployment year but also significantly across market scale indicators, notably cumulative capacity, total power generation, and population. These market-scale features define the primary inter-cluster differences in SHAP contributions, whereas local wind resource endowments (e.g., wind speed, wind yield, and wind power density) remain consistent across the subgroups.

The temporal dynamics of these feature contributions are further revealed in Fig. S10. Across both technologies, high equipment prices (module and turbine) dominate the upward predictive contributions to costs during the early periods (Cluster 1). However, the pathways to cost reduction diverge in recent, low-cost regimes. For solar PV, the sustained downward SHAP contributions are overwhelmingly associated with deployment year and module price. For onshore wind, while one recent regime relies similarly on turbine price reductions, another distinct regime demonstrates massive cost reductions strongly associated with accumulated market scale and population capacity.

In summary, these SHAP-defined clusters encapsulate the fundamental divergence in cost-evolution paradigms between the two technologies. For solar PV, the three clusters represent a globally synchronized, linear progression: (1) Cluster 1, a legacy high-cost regime; (2) Cluster 2, a transitional phase; and (3) Cluster 3, a mature, technology-driven low-cost regime. In contrast, onshore wind presents a divergent, dual-track structure comprising: (1) Cluster 1, a legacy price-penalized regime; (2) Cluster 2, a recent technology-led regime; and critically, (3) Cluster 3, a unique scale-driven regime. This distinction highlights that while solar PV costs are universally dictated by global technology learning, onshore wind offers an independent, localized pathway to cost competitiveness through massive domestic market scale and infrastructure.

Note S3: Take-off year identification

We determined the take-off year using a predefined reconciliation framework based on the Formative phase Bayesian change-point Indicator (FOBI)[1] and a cascade-gated model. The FOBI year is adopted if both methods align within a ±2-year margin or if only FOBI detects a take-off. Historical calibration is required if the methods diverge by more than two years or if only the cascade-gated model identifies a take-off.

The discrepancy between the two models often arises from insufficient signal-to-noise ratios during the sporadic phase of deployment. In countries with negligible initial capacity, the pre-commissioning period fails to cross the FOBI's prior threshold for a 'formative phase'. The FOBI algorithm typically treats these periods as a quiescent baseline, and abrupt transitions directly from baseline to mass deployment are not captured within its regime-switching logic. This divergence highlights the complementary nature of the two approaches. FOBI is designed to detect structural shifts in underlying growth processes, whereas the cascade-gated model identifies when cumulative capacity crosses specific triggers. In early-adopting or mature markets that experienced a gradual formative phase, both models typically capture the take-off, and any minor discrepancies reflect the natural ambiguity between policy enactment and capacity milestones—resolvable via historical calibration. Conversely, in 'step-function' markets characterized by instant entry, the FOBI naturally returns an 'NA' because a gradual formative phase is absent. In such scenarios, the cascade-gated model's detection reflects an abrupt commissioning marker rather than a fundamental change in the long-term growth trajectory.

(1) Primary benchmark

We adopted the take-off years from Jakhmola, et al. [1] as our primary benchmark. The FOBI marks the transition from sporadic to sustained deployment by detecting the earliest statistically significant change point via piece-wise Bayesian regression and model averaging. This probabilistic design explicitly avoids the arbitrary penetration cut-offs typical of threshold-based approaches.

(2) Supplementary detection: cascade-gated model

We developed a cascade-gated model to cover countries absent from the FOBI sample and to flag disagreements that warrant closer inspection. Specifically, for every country we constructed an annual penetration series, defined as cumulative installed capacity divided by total grid capacity, and retained countries with at least five post-entry observations. Countries were stratified by contemporaneous grid size into Small (<20 GW), Medium (20-

100 GW), and Large (>100 GW) regimes. This stratification ensures our model accounts for the sharply differing absorption limits and expansion dynamics across varying grid SCALE. While the same overarching detection architecture was applied to both solar PV and onshore wind, thresholds were calibrated separately to reflect their distinct deployment cycles, learning curves, and historical cost-collapse eras.

Take-off year detection utilized a hybrid cascade model, combining endogenous statistical testing with deterministic physical rules. Each country exited the cascade at the first satisfied condition: (a) Legacy early movers observed before the start of the respective dataset (2000 for onshore wind, 2010 for solar PV) and already exceeding the stratum-specific penetration floor were assigned a take-off year equal to the first year of data availability. (b) For remaining countries, we applied the Bai-Perron structural-break test with minimum segment length h=3 and up to two breaks to a regression of the base-10 logarithm of penetration on year, an approach that locates endogenous regime shifts without pre-specifying their timing. Each candidate break was retained only if the country passed stratum-specific physical filters on future penetration level, compound annual growth rate over the subsequent window, and the ratio of annual new capacity to grid size. (c) Countries entering the panel already above the penetration floor were classified as instant-entry take offs, and those failing all rules were labelled as not yet taken-off.

Under the Base scenario, the Small-grid penetration floor was set to 1.0% for both technologies, while Medium- and Large-grid floors rose from 1.5% and 2.0% for onshore wind to 2.0% and 3.5% for solar PV. The required compound annual growth rate in Medium and Large grids rose from 15% for onshore wind to 20% for solar PV, and the Small-grid new-capacity-to-grid ratio doubled from 2.5% to 5.0%. Together, these stricter solar thresholds reflect the steeper deployment ramps of the post-2010 cost-collapse era and prevent overcounting of solar takeoffs while preserving sensitivity to earlier and slower wind transitions. Diffusion speed was defined as the average annual increase in penetration during the six-year window beginning in the take-off year, measured as the slope coefficient from an ordinary least-squares regression of the base-10 logarithm of penetration on calendar year.

We further conducted sensitivity and robustness tests to evaluate the classification under three threshold scenarios for each technology, spanning the plausible parameter space. The *Relaxed* scenario lowered all penetration and growth thresholds by 25–50% to capture weak acceleration signals, whereas the *Strict* scenario raised them by similar proportions to exclude subsidy-driven pseudo-takeoffs lacking sustained momentum. Robustness was evaluated based on two metrics. Quantity fluctuation was defined as the absolute change in the take-off country count relative to the Base scenario, with classifications considered robust at ≤25%. Temporal stability was defined as the share of jointly classified countries whose take-off year shifted by ≤2 years between scenarios, with classifications deemed consistent at ≥80%. Across both technologies and both off-Base scenarios, 94.0–97.0% of jointly classified countries retained their takeoff year within ±2 years of the Base assignment, and takeoff-country counts varied by at most 25% (solar PV: 33–54; onshore wind: 41–60), confirming that our stratified, physically-constrained classification architecture is relatively robust across the plausible threshold space (Table S1).

(3) Historical calibration

Historical calibration rests on two evidentiary pillars. The first is documented policy causation: the specific legislative or regulatory instrument that triggered sustained market expansion. The second is physical deployment verification: confirmation that planned capacity reached commissioning. We cross-checked deployment evidence against installed-capacity records, generation shares, and project commissioning records from national energy ministries and grid operators.

FOBI and cascade-gated model disagree in countries showing either early policy signals without follow-through or long formative phases interrupted by multiple policy waves. Numerical thresholds cannot resolve these cases without circular reasoning, because the same growth data that drive FOBI and cascade-gated model would also determine any threshold outcome. Exogenous policy chronologies and commissioning records provide an independent basis for adjudication.

We defined the calibrated take-off year as the first calendar year when three conditions were met simultaneously. The enabling policy instrument had to be operational rather than merely legislated. The first commercial-scale projects had to reach commissioning. Annual capacity additions had to enter a sustained multi-year expansion, as documented in national grid reports or international databases. Country-level decisions, supporting evidence, and final assigned years are reported in Tables S2-5.

(4) Reconciliation results

Following the reconciliation process, a subset of countries required historical calibration (Step 3) to determine their takeoff years.

For solar PV, 24 countries underwent historical calibration (Tables S2, S3). Driven by the 2010 baseline rule, early adopters whose initial deployment signals emerged prior to 2010, namely Germany (2008), Spain (2008), Belgium (2009), and Portugal (2009), were uniformly adjusted to 2010. Similarly, Austria and Greece were calibrated to 2010. The calibrated takeoff years for the remaining 18 nations span from 2011 to 2017. This distribution captures a diverse wave of global diffusion, ranging from early followers (such as Ukraine in 2011 and Romania in 2012) to later entrants heavily concentrated in the latter half of the 2010s (such as El Salvador, Hungary, the UAE, and Vietnam in 2017).

For onshore wind, historical calibration was conducted for 9 countries (Tables S4, S5). Adhering to the 2000 baseline rule, Denmark, a recognized pioneer with formative activities dating back to 1991, was adjusted to the year 2000. The calibrated takeoff years for the remaining 8 countries range from 2004 to 2014. This chronological spread effectively captures the sequential expansion of onshore wind, advancing from early adopters in the 2000s (such as New Zealand in 2004, Ireland in 2006, and Estonia in 2007) to emergent Central American markets in the subsequent decade (such as Honduras in 2011, Costa Rica in 2014, and Panama in 2014).

Note S4: Cascade-based stage assignment and pathway classification

We applied the algorithm separately to the global distribution of four indicators: annual new capacity (two classes on log scale), installation cost (three classes), cumulative capacity (three classes on log scale), and penetration (three classes). Penetration is calculated as the ratio of cumulative installed capacity to total grid capacity. Log-transformation of capacity metrics prevented high-deployment outliers from dominating the break optimisation.

(1) Rule cascade for stage assignments

Every country-year observation was assigned to one of six deployment stages through a priority-ordered rule cascade evaluated top-to-bottom. The cascade prevents established deployers from being misclassified as nascent during transient cost fluctuations by prioritizing scale and penetration criteria over cost-based categories. The rules are as follows:

- Mature Penetration (MP): Assigned when penetration exceeded the upper band, or cumulative capacity crossed the elite threshold while installation cost remained in the lowest band.
- Accelerating Growth (AG): Captured country-years with annual additions above the scale threshold, mid-range penetration, or elite cumulative capacity at mid-range cost.
- Policy-Driven Scaling (PS): Flagged high-volume or elite-capacity deployment sustained at cost in the upper band, indicating subsidy dependence[10,11].

- Cost Parity (CP): Marked small-volume deployment at lowest-band cost, characteristic of late entrants exploiting global learning spillovers.

- Formative Phase (FP): Denoted small-volume deployment at upper-band cost.

- Early Adoption (EA): Absorbed all remaining country-years not meeting the above criteria.

(2) Sequence compression and trajectory identification

National trajectories were identified by compressing each country's annual stage sequence into a symbolic string. Consecutive identical stages were collapsed via run-length encoding (e.g., a trajectory of FP-FP-FP-EA-EA-PS-PS-AG-AG-AG-MP was compressed to FP-EA-PS-AG-MP).

Countries were then classified through ordered regular-expression matching. The cascade was evaluated in the sequence: Front-Runners, Leapfroggers, Gradualists, and Laggards:

- Front-Runners (Path A): Strings beginning with AG or MP before a technology-specific pioneer cutoff year (2005 for onshore wind, 2012 for solar PV). For solar PV, this also admits sequences from PS to AG/MP before the cutoff, capturing feed-in-tariff-driven European pioneers.

- Gradualists (Path B): Countries reaching AG/MP without passing through PS or CP.

- Leapfroggers (Path C): Countries entering directly at AG/MP after the cutoff, or traversing CP before stabilizing in AG/MP.

- Laggards (Path D): Reached CP but failed to sustain AG or MP.

Residual countries unmatched by any rule were diagnosed as stuck in early stages, policy collapses (AG/MP followed by regression without buffering), or data-sparse trajectories. As noted in the main text, Paths B and C collapsed into 'Late Movers' for onshore wind.

(3) SHAP-based validation of stage assignments

We validated the C-SPDM stage assignments through unsupervised k-means clustering on country-year SHAP values extracted from the random-forest cost-imputation model. Clustering the SHAP matrix yielded three robust clusters for both technologies. Cross-tabulation against the heuristic C-SPDM stages revealed strong statistical concordance, which was formally confirmed by Pearson chi-square residuals (Figs. S14-17).

For solar PV, Cluster 1 spanned only the three earliest stages (100% of FP, 99% of EA, 100%

of PS, residual 20.71*** at EA), Cluster 2 split CP (58%) and AG (38%), and Cluster 3 dominated MP (63%, residual 9.25***) (Figs. S14, 15). This pattern reflects an earlier and more gradual driver transition, consistent with globally tradable PV module markets that allow late entrants to access mature supply chains and shift cost determinants well before reaching CP.

For onshore wind, Cluster 1 dominated the four early-to-acceleration stages (100% of FP, 98% of PS, 73% of AG), Cluster 2 captured 62% of CP (residual 2.38***) and 61% of MP, and Cluster 3 emerged exclusively in MP (24%, residual 18.38***) (Figs. S17, 18). This pattern indicates that wind cost determinants remain structurally homogeneous from market entry through scale-up, then pivot abruptly at CP as domestic supply chains and learning-by-doing displace turbine import dependence as the dominant driver.

Note S5: Distributional of penetration and learning rates across deployment stages

As shown in Fig. S34, solar PV and onshore wind penetration rates increased monotonically across successive deployment stages for both developed and emerging economies. However, their learning rate trajectories diverged sharply by technology. While solar PV maintained robust positive median learning rates across almost all stages, onshore wind yielded near-zero or negative median learning rates in early and transitional phases before finally recovering at the mature stage.

For solar PV, median penetration rates scale progressively from the FP (0.02%) and EA (0.05%) to CP (0.21%), PS (0.26%), AG (0.96%), and ultimately MP (3.36%) (Fig. S34a). Excluding the EA phase (where the overall median temporarily peaks at 25.30%), median solar PV learning rates generally mirror this sequential expansion, ascending from the PS (8.69%) to AG (17.76%), and MP (24.71%) (Fig. S34c). Furthermore, while the penetration gap between developed and emerging economies remains relatively stable across stages, disparities in learning rates become highly pronounced during AG and MP, with developed economies achieving 30.12% and 33.64% compared to 16.92% and 24.71% for emerging economies.

For onshore wind, excluding the initial FP, median penetration levels similarly follow an ascending order across the remaining stages. Notably, onshore wind achieves significantly higher absolute penetration levels than solar PV during PS (1.76%), AG (4.81%), and MP (6.57%) (Fig. S34b). In stark contrast to its penetration growth, onshore wind learning rates exhibit stagnation during PS and FP stages, where learning rates are less than 0 (Fig. S34d).

Note S6: C-SPDM based Monte Carlo projection

The C-SPDM-based Monte Carlo model integrates path- and stage-conditions to project country-level installed costs for solar PV and onshore wind from 2023 to 2050 under five policy scenarios. The model incorporates three empirical components: a development-path classifier that captures fixed national attributes, a six-stage technology-diffusion classifier that evolves dynamically over the simulation horizon, and a hierarchical parameter-lookup system that draws capacity growth, learning rate, and penetration change from country-year historical observations. Wright's Law translates capacity expansion into cost reduction at each annual step. Stochastic perturbations across 100 simulation runs propagate parameter uncertainty into 90% confidence intervals around projected costs.

Two technology-specific adaptations are reconciled with empirical heterogeneity observed between solar PV and onshore wind. The two divergences (path merging and learning-rate stratification) are detailed before the shared mechanics are described.

(1) Technology-specific adaptations

Solar PV and onshore wind diverge along two dimensions of the parameter-estimation process, while sharing the diffusion model, the physical constraints, and the Monte Carlo simulation. The first divergence concerns developmental-path resolution. Solar PV retains all four paths (Path A: Front-Runners; Path B: Gradualist; Path C: Leapfroggers, Path D: Laggards) because each path contains sufficient country-year observations to support stable parameter estimation. Onshore wind merges Paths B and C into a single "Late Movers" category (Path B/C) because the Leapfrogger sample is too small to support independent estimation, and the two groups display similar stage trajectories in the historical record.

The second divergence concerns the stratification of learning rates. Learning rates for solar PV are estimated jointly across pathways and stages, allowing the cost-reduction elasticity to vary during the diffusion process. Onshore wind learning rates perform poorly at the stage level, with most stages showing stagnation (Fig. S32d). Therefore, we aggregate learning rates only by pathway and use country-level estimates based on Wright's Law. This adjustment eliminates spurious signals at the stage level, which would otherwise propagate noise into the cost projections. These two divergences are summarised in Table S8 for reference.

(2) Hierarchical parameter estimation

A three-tier lookup system is used to estimate changes in capacity growth, learning rates, and penetration rates for each country-year combination under every path-stage combination.

The first tier returns the median of country-year observations that match both the simulated country path and stage (path × stage cells). When there are no observations in a "path × stage" cell, the second level returns the median for the path alone. When the path level is also empty, the third level returns the global median across all countries. This hierarchical structure preserves stage-specific signals where data permit, while smoothly downgrading to broader aggregated data for sparse cells. For solar PV, all three parameters employ a complete cascade model consisting of Tier 1 → Tier 2 → Tier 3. For onshore wind, installed capacity growth and penetration change retain the cascade, but learning rate is instability at the stage level and therefore omits Tier 1. Three empirical observations support this adjustment.

(3) Physical and dynamic constraints

In each annual step, four physical constraints limit the projected trajectory. The lower bound for hardware costs is 150$/kW for solar PV and 600/$kW for onshore wind. A penetration ceiling of 100% caps the share of electricity supplied by each technology. A stage-specific growth ceiling, ranging from 100% in the Formative Phase to 15% in Mature Penetration, prevents implausible capacity expansion in late-stage countries. A learning-rate band of 5–35% for solar PV and 2–30% for onshore wind brackets observed cost-reduction elasticities in the literature.

Dynamic ceilings further allow countries with exceptional historical performance to exceed the baseline physical caps. For each path-and-stage cell with sufficient observations, the model computes the empirical 75th percentile of capacity growth and learning rate. The effective ceiling in any simulation step equals the maximum of the baseline physical cap and the cell-specific 75th percentile. This rule prevents the baseline caps from artificially censoring trajectories that historical Front-Runners have already demonstrated to be feasible.

(4) Monte Carlo simulation

For each scenario, parameter uncertainty is propagated from 2023 to 2050 through 100 random simulations. The first run uses the median of the deterministic parameters directly. Each subsequent run applies zero-centered independent Gaussian noise perturbations to changes in growth rates, learning rates, and penetration rates. The standard deviation of each perturbation equals half of the path-level cross-country standard deviation, with hard fallback values of 0.05, 0.03, and 0.002 when path-level standard deviations are missing. Before the start of each annual step, the perturbed parameters are re-constrained within the dynamic bounds.

State variables are updated sequentially at each annual step. Cumulative installed capacity grows at the perturbed growth rate. Penetration increases by the perturbed annual change, capped at 100%. Costs evolve according to Wright's law. Subsequently, the stage classifier re-evaluates the country's stage based on the updated state, thereby determining the parameter set for the following year. This recursive structure allows countries to transition endogenously between stages as their costs, installed capacity, and penetration evolve.

(5) Sensitivity analysis

The multiplicative sensitivity test perturbs the growth rates and learning rates at all path levels using coefficients of 0.8, 1.0, and 1.2. For each coefficient, the development trajectory for 2023–2050 is projected through 30 simplified simulation runs under the BAU scenario. Subsequently, the average costs in 2050 under different multipliers and development pathways are compared. This test aims to isolate and analyze how proportional changes in input parameters translate into changes in long-term cost outcomes, thereby validating the external validity of the deterministic forecasts (Fig. S39).

Note S7: Robustness check

Because cumulative installed capacity is used in the subsequent learning-curve analysis, we tested whether the random-forest cost projections were sensitive to including this variable in the cost-prediction models. As a robustness check, we re-trained the random-forest cost models after excluding cumulative installed capacity from the predictor set, while keeping the remaining variables and model settings unchanged. We refer to the estimates from the main specification as the baseline estimates and those from the capacity-exclusion specification as the robust estimates.

We evaluated the consistency between the two specifications using three complementary diagnostics. First, we compared their prediction errors to assess whether excluding cumulative installed capacity materially changed model performance. Second, we used Bland–Altman analysis to evaluate the agreement between the baseline and robust estimates across the full range of predicted costs. Third, we compared the distribution of predicted installed costs along cumulative installed capacity to examine whether the main cost–capacity patterns were preserved.

For the Bland–Altman analysis, we calculated, for each country-year observation, the mean of the two estimates as

$$Mean = (Baeline\ estimate + Robust\ estimate)/2 \qquad (2)$$

and their difference as

$$Difference = Robust\ estimate - Baeline\ estimate \quad (3)$$

The mean difference represents the average bias between the two specifications. A value close to zero indicates that excluding cumulative installed capacity does not systematically increase or decrease the predicted cost. The limits of agreement were calculated as the mean difference ±1.96 standard deviations of the differences. These limits indicate the range within which most differences between the baseline and robust estimates are expected to fall. Plotting the differences against the mean estimates further allows us to examine whether the discrepancy between the two specifications varies across the cost range.

The results show that excluding cumulative installed capacity had little effect on the random-forest cost projections. Fig. S47 shows that excluding cumulative installed capacity has little effect on random-forest predictive performance (Fig. S2). For solar PV, the test-set R^2 changes from 0.878 in the baseline model to 0.884 in the capacity-exclusion model, while the test-set RMSE changes from 0.202 to 0.197. For onshore wind, the corresponding test-set R^2 changes from 0.63 to 0.615, and the RMSE changes from 0.145 to 0.148. The training-set metrics show similarly small differences, indicating that the robustness specification preserves the predictive performance of the main model.

Fig. S48 directly compares the baseline and robust cost estimates. For solar PV, the two sets of estimates are highly aligned, with an R^2 of 0.994 and an RMSE of 0.134 2025 US$/kW. The Bland–Altman comparison shows a small negative bias of −0.08 US$/kW), indicating that the capacity-exclusion model predicts slightly lower costs on average than the baseline model. For onshore wind, the agreement is also strong, with an R^2 of 0.981 and an RMSE of 0.053 US$/kW). The mean Bland–Altman bias is approximately zero, indicating no systematic difference between the two specifications. In both technologies, most observations fall within the limits of agreement, and there is no substantial systematic divergence across the predicted cost range.

Fig. S49 further shows that the main distributional patterns are preserved (Fig. 1). The country-level distribution of predicted costs remains similar between the two specifications, and the cost–capacity distributions retain their original shapes. Solar PV continues to show a monotonic decline in predicted installed cost with cumulative installed capacity, whereas onshore wind retains an inverted-U-shaped relationship. These results suggest that the main learning-curve patterns are robust to excluding cumulative installed capacity from the random-forest predictor set.

Together, these robustness checks indicate that the cost projections are robust to the exclusion of cumulative installed capacity. This reduces concerns that the subsequent learning-curve estimates are biased by using cost projections that depend directly on cumulative deployment.

Supplementary Figures

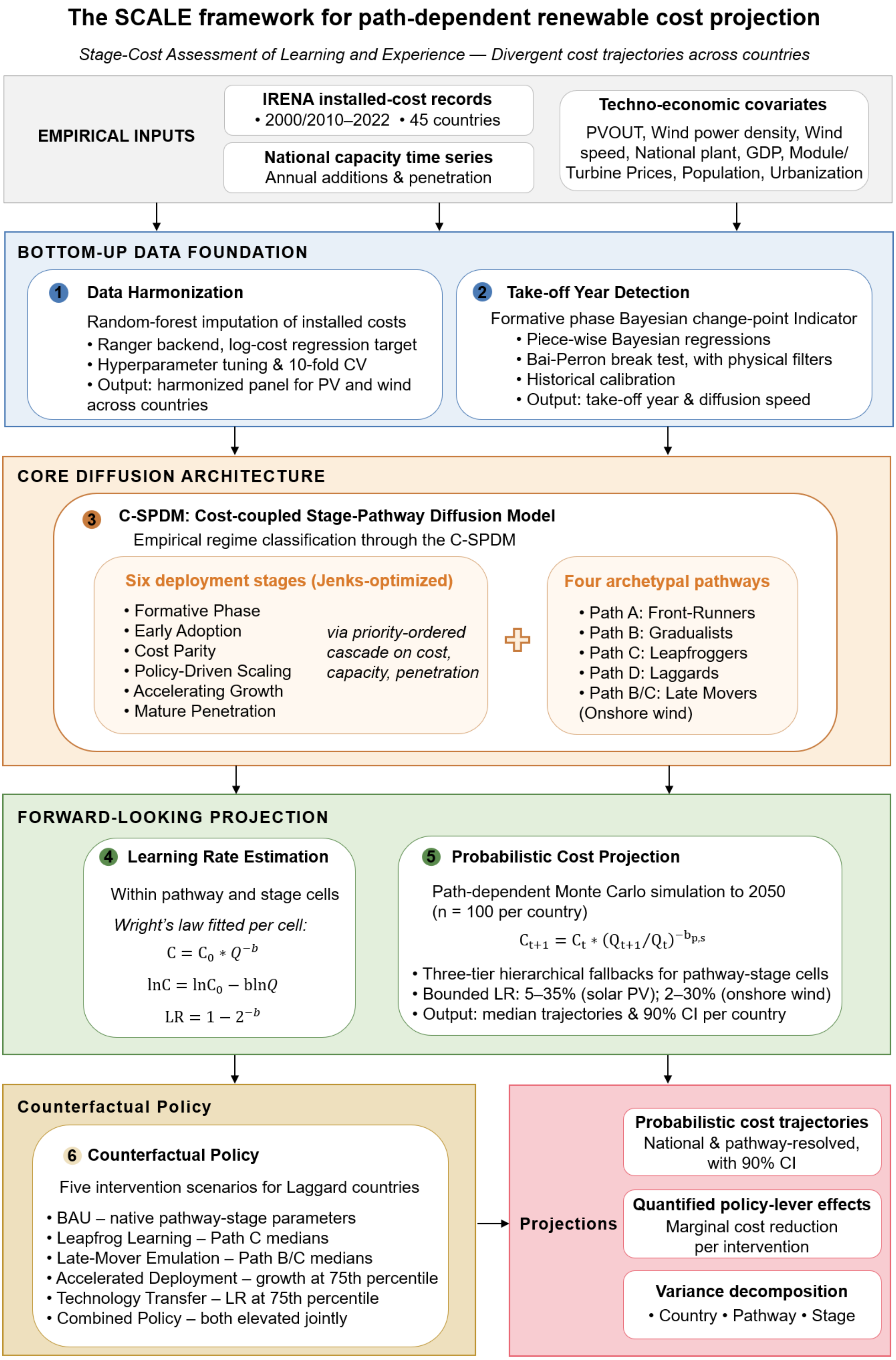


Fig. S1. The SCALE framework for path-dependent renewable cost projection

SCALE (Stage-Cost Assessment of Learning and Experience) integrates six steps to project country-resolved installed costs of utility-scale solar PV and onshore wind to 2050 from harmonized empirical inputs. Three bottom-up steps build the empirical foundation: data harmonization (Step 1), take-off year identification (Step 2), and the Cost-coupled Stage-Pathway Diffusion Model (C-SPDM, Step 3) that classifies country-years into six deployment stages and four archetypal pathways through priority-ordered cascades and regex matching on run-length-encoded stage strings. Two forward-looking steps generate trajectories: Learning rate estimation (Step 4) and probabilistic cost projection (Step 5) running 100 trajectories per country with three-tier fallbacks and bounded learning rates. Counterfactual policy simulation (Step 6) perturbs growth and learning parameters of Laggard countries (Path D) to the 75th-percentile benchmark of successful pathways across five intervention scenarios. Inputs include IRENA installed-cost records, national capacity time series, and techno-economic covariates (PVOUT, wind power density, wind speed, GDP/GDP per capita, national plant counts, global component prices, population, urbanization). Outputs comprise probabilistic country-level cost trajectories with 90% confidence intervals, variance decomposition of 2050 cross-country cost dispersion, and quantified marginal effects of each policy lever. LR, learning rate; BAU, business-as-usual; CI, confidence interval.

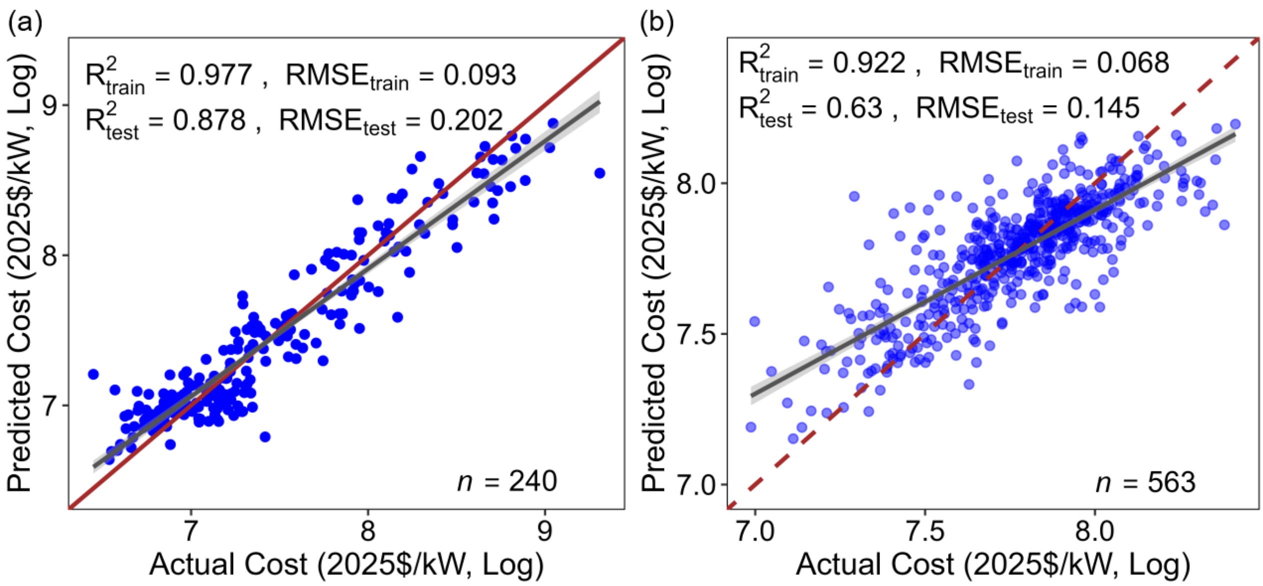


Fig. S2. Predicted and actual log-transformed installed costs for solar PV and onshore wind random forest models.

(**a**) Predicted against actual log-transformed solar PV installed cost with cumulative capacity as a predictor (2022 \$ kW^{-1}; n=241). (**b**) Predicted against actual log-transformed onshore wind installed cost with cumulative capacity as a predictor (n=563). Blue points denote individual country-year observations for testing dataset, the grey line shows the ordinary-least-squares fit with its 95% confidence band, and the red diagonal indicates the 1:1 reference. In-panel statistics report the coefficient of determination (R^2) and root-mean-square error (RMSE) on the training and held-out test partitions. RMSE is expressed in log-cost units.

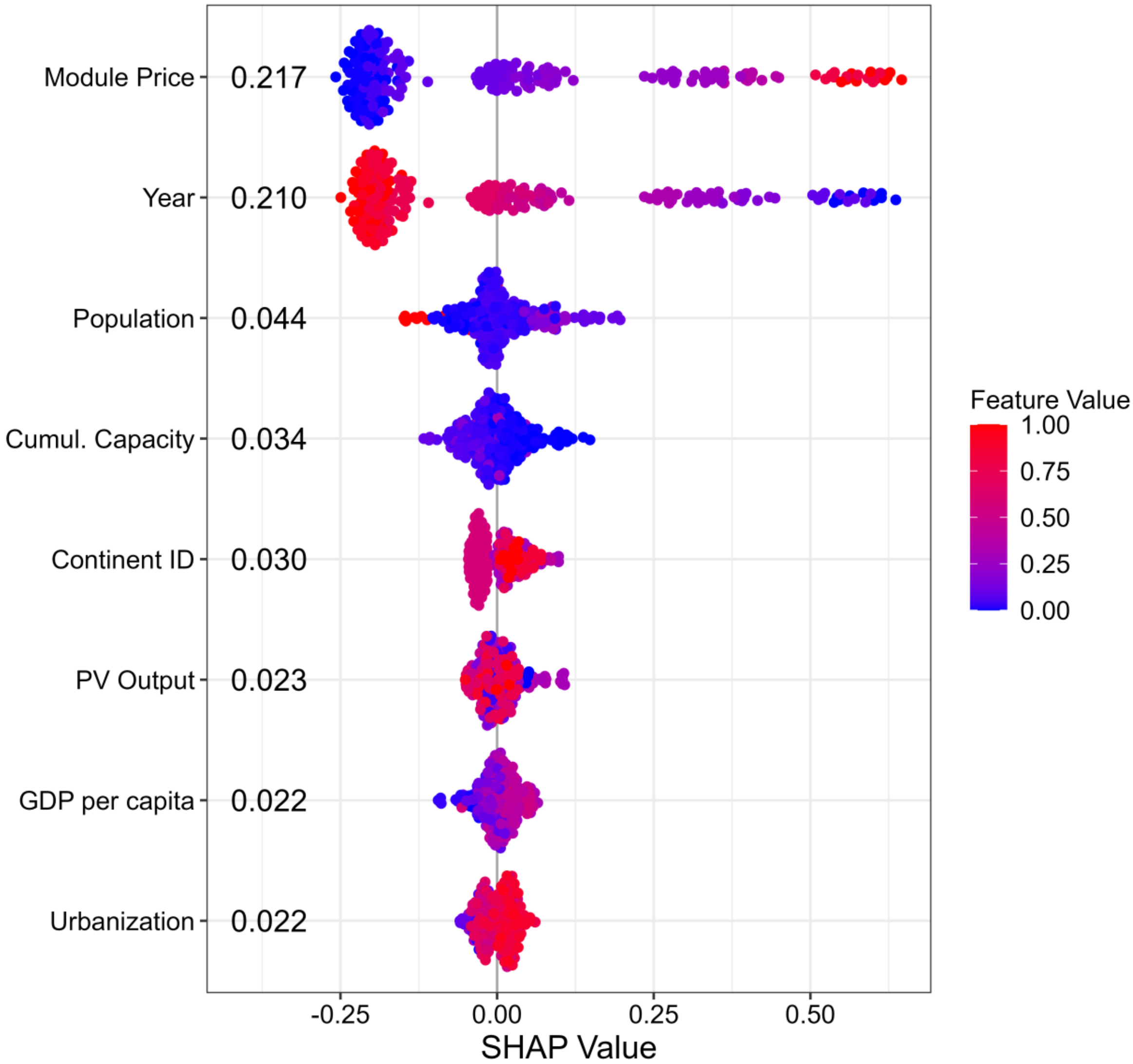


Fig. S3. SHAP feature importance and value distributions for random-forest model of solar PV installation cost

SHAP summary plot for the solar PV installation cost random forest model, with features ranked by mean absolute SHAP value (shown beside each feature name). Each point represents a country-year observation, with horizontal position giving the SHAP contribution to predicted installation cost and colour encoding the min-max-normalised feature value (blue, low; red, high). Vertical jitter indicates local point density. SHAP, SHapley Additive exPlanations.

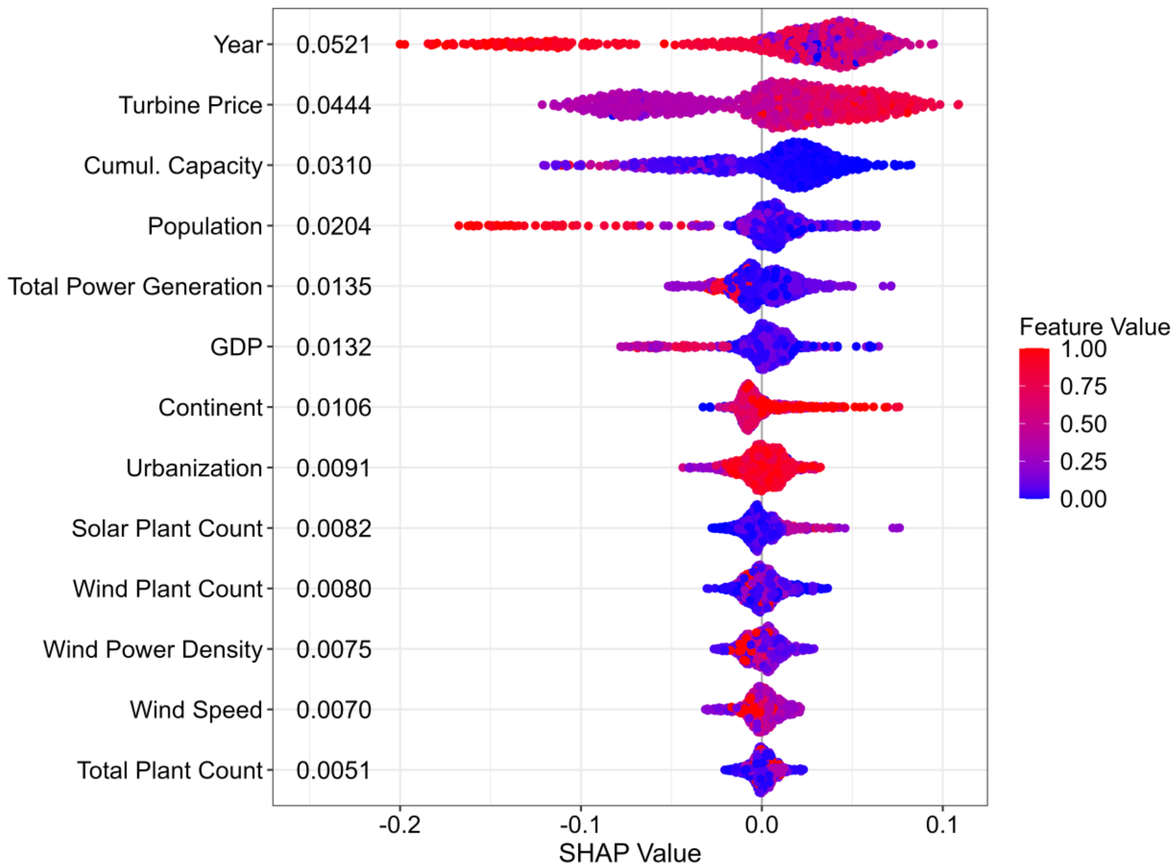


Fig. S4. SHAP feature importance and value distributions for random-forest model of onshore wind installation cost

SHAP summary plot for the onshore wind installation cost random forest model, with features ranked by mean absolute SHAP value (shown beside each feature name). Each point represents a country-year observation, with horizontal position giving the SHAP contribution to predicted installation cost and colour encoding the min-max-normalised feature value (blue, low; red, high). Vertical jitter indicates local point density. SHAP, SHapley Additive exPlanations.

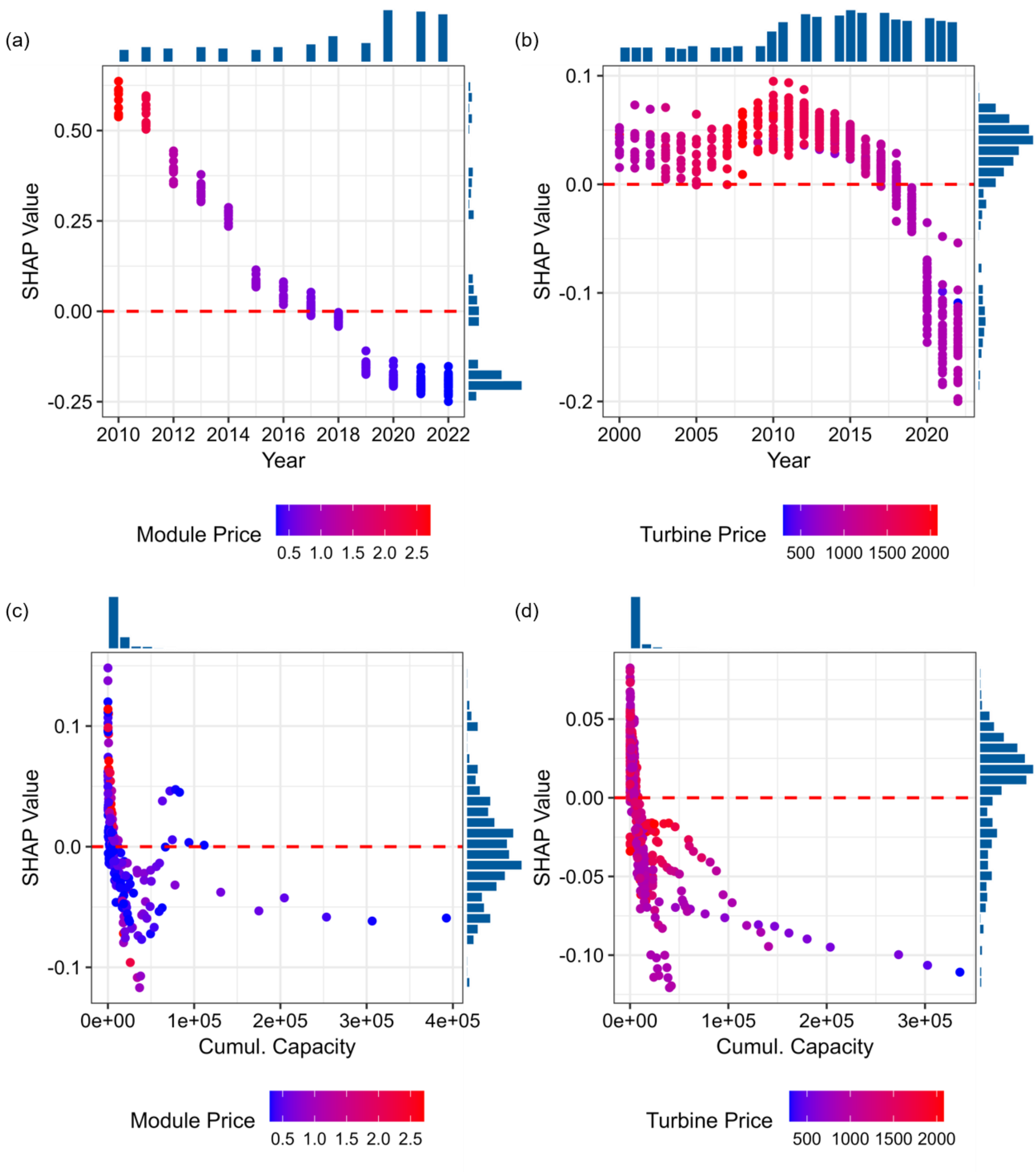


Fig. S5. SHAP dependence of solar PV module and wind turbine prices on deployment year and cumulative capacity.

(**a**) SHAP values for solar PV installation cost against deployment year, with point colour indicating installation cost (2022 \$ W^{-1}). (**b**) SHAP values for onshore wind installation cost against deployment year, coloured by installation cost (2022 \$ kW^{-1}). (**c**) SHAP values for solar PV installation cost against cumulative installed solar PV capacity (MW). (**d**) SHAP values for onshore wind installation cost against cumulative installed wind capacity (MW). SHAP values quantify the marginal contribution of each feature to predicted installation costs, derived from a random forest regression trained on country-year technology-cost records. Marginal histograms on the top and right axes display feature and SHAP-value distributions, respectively. Red dashed lines mark a zero SHAP contribution. SHAP, SHapley Additive exPlanations.

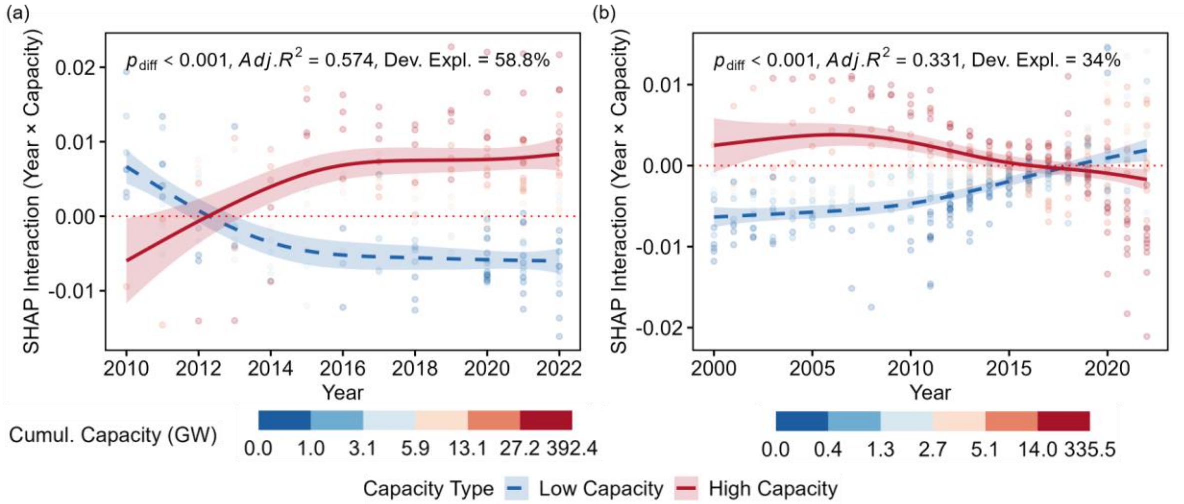


Fig. S6. SHAP interaction values between deployment year and cumulative capacity for the log-transformed installation costs of solar PV (a) and onshore wind (b).

Points denote individual country-year observations coloured by cumulative installed capacity (GW), partitioned at the median into low-capacity (blue) and high-capacity (red) groups. Solid and dashed curves show generalised additive model (GAM) fits for each group, with shaded bands indicating 95% confidence intervals. The red dotted line marks a zero-interaction contribution. In-panel statistics report the p value for the difference between group-specific smooth terms (p_{diff}), the adjusted coefficient of determination (Adj. R^2), and the deviance explained (Dev. Expl.) of the GAM. SHAP, SHapley Additive exPlanations; GAM, generalised additive model.

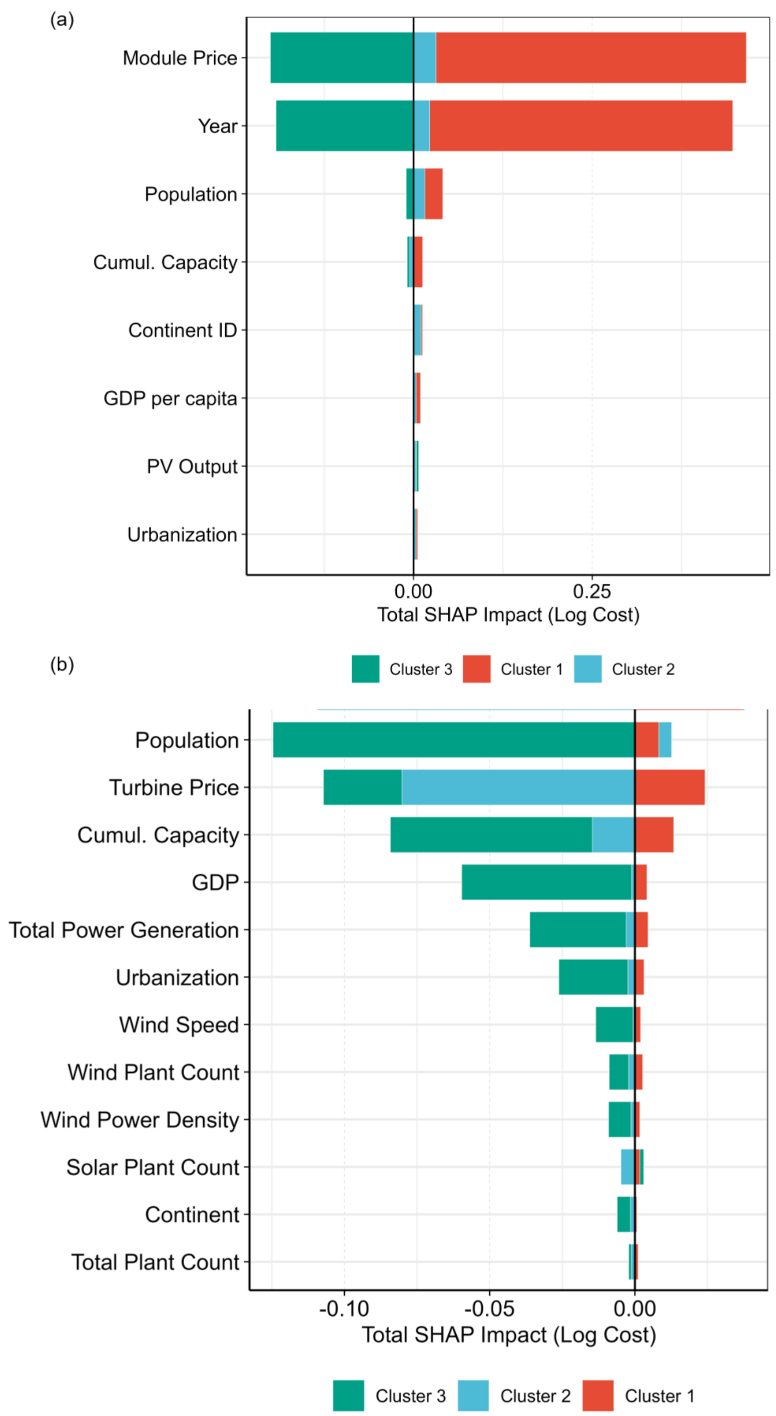


Fig. S7. Clustered SHAP feature contributions to solar PV and onshore wind installation costs (a) Cluster-stratified total SHAP on predicted log solar PV installation cost (log \$ kW^{-1}), with features ranked by overall absolute contribution. (b) Corresponding cluster-stratified total SHAP on predicted log onshore wind installation cost (log \$ kW^{-1}). Bars give the sum of SHAP values within each cluster for each feature, so bar length encodes both the magnitude and sign of the cluster's aggregate contribution to predicted cost. Clusters were obtained by k-means partitioning of the per-observation SHAP value matrix from the RF installation cost models, capturing distinct cost-formation regimes across country-year records. The vertical black line marks zero net SHAP contribution. SHAP, SHapley Additive exPlanations.

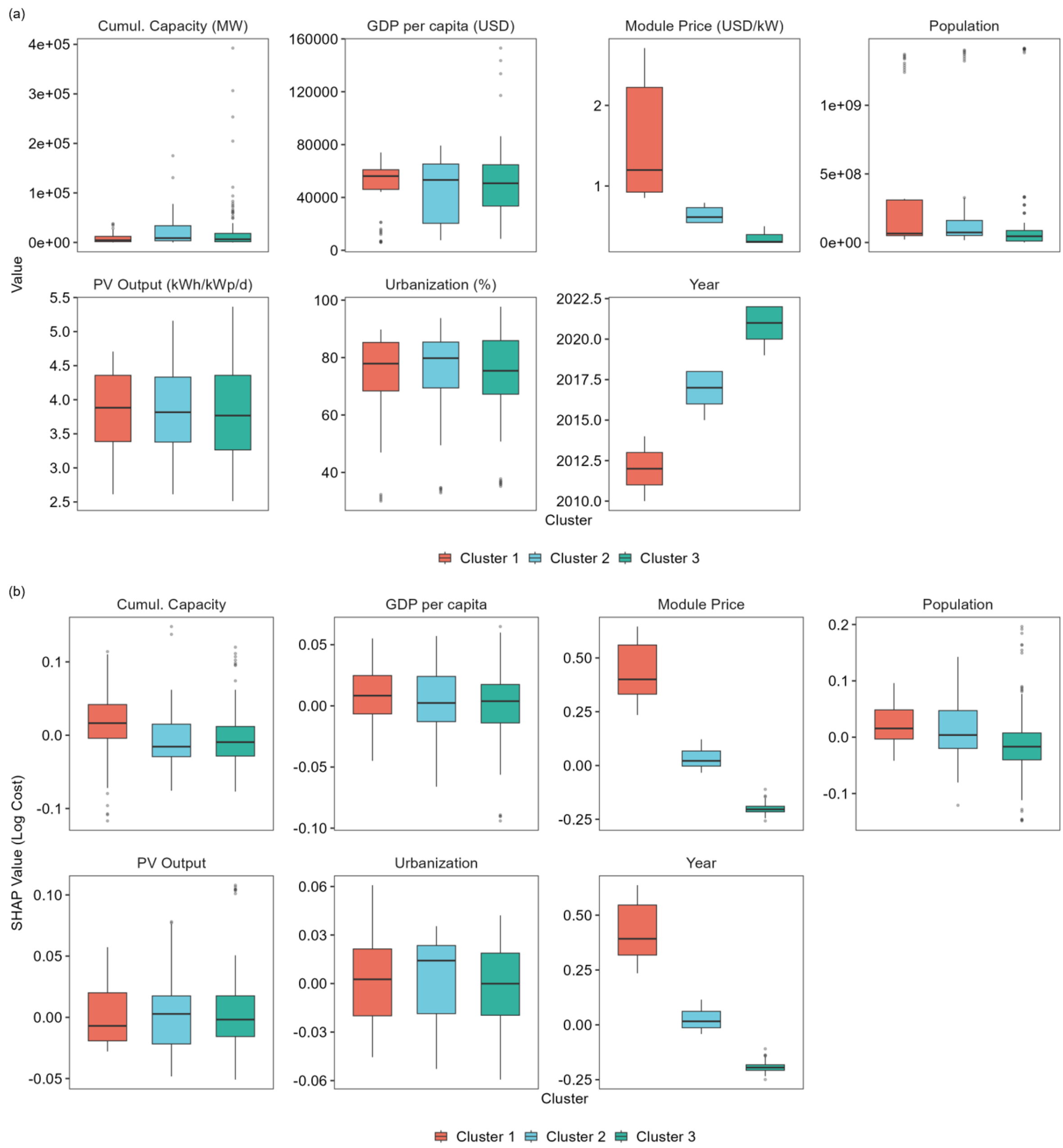


Fig. S8. Cluster-wise feature value and SHAP value distributions for the solar PV installation cost model

(**a**) Distributions of raw feature values across the three clusters for cumulative installed capacity (MW), GDP per capita (2025$), module price (2025$/kW), population, PV output (kWh/kWp/d), urbanisation (%), and deployment year. (**b**) Corresponding distributions of per-feature SHAP values (log 2025$/W) on predicted solar PV installation cost for the same clusters and features. Boxes span the interquartile range (IQR) with the central line marking the median, whiskers extend to 1.5 × IQR, and points beyond denote outliers. Clusters were obtained by k-means partitioning of the per-observation SHAP value matrix from the random forest installation cost model. Cluster 1 (red), Cluster 2 (blue), Cluster 3 (green) correspond to early-period high-cost, mid-period transitional, and recent low-cost country-year regimes, respectively.

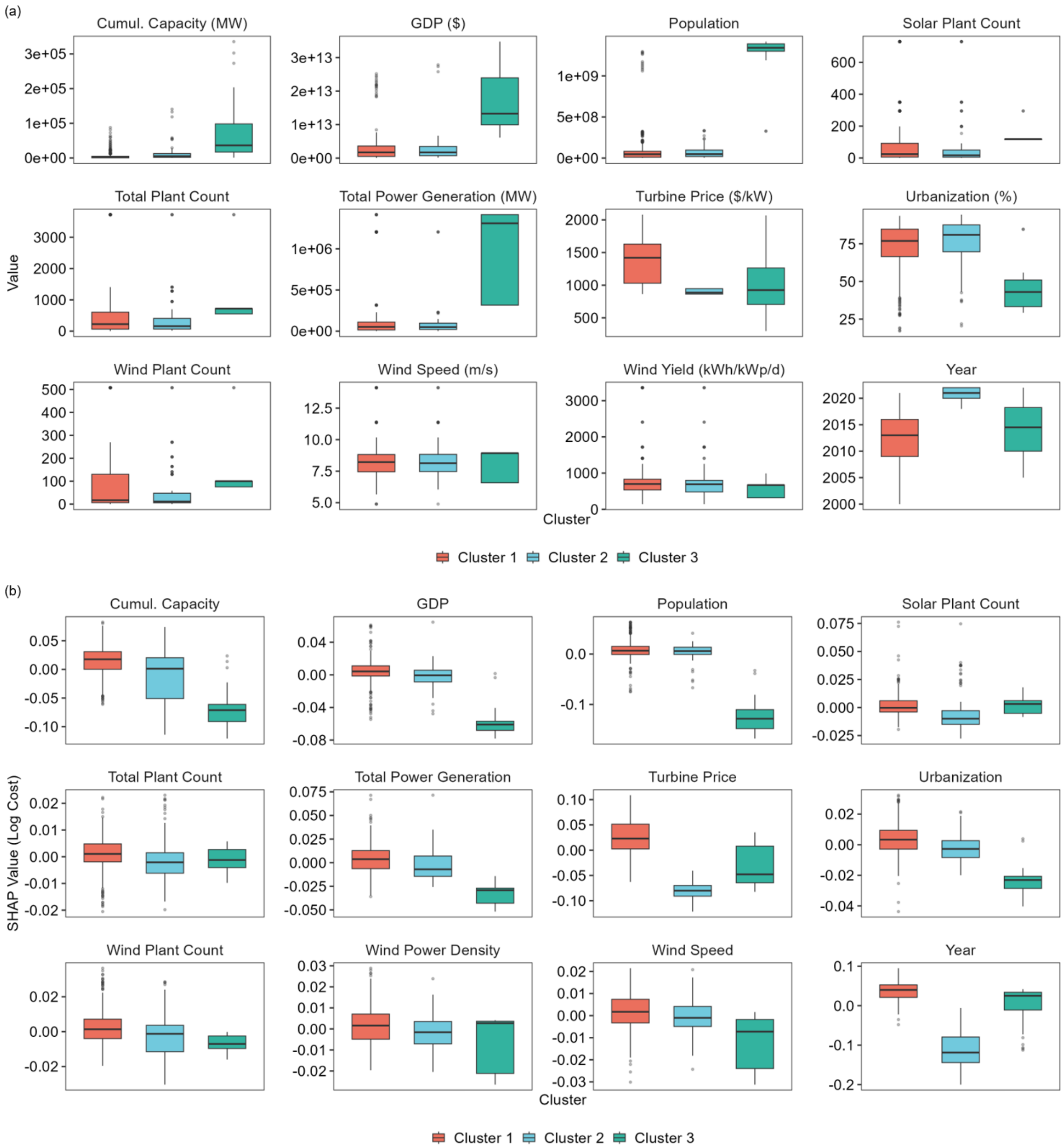


Fig. S9. Cluster-wise feature value and SHAP value distributions for the onshore wind installation cost model

(a) Distributions of raw feature values across the three clusters for cumulative installed capacity (MW), GDP (2025$), population, solar plant count, total plant count, total power generation (MW), turbine price (2025$/kW), urbanisation (%), wind plant count, wind speed (m/s), wind yield (kWh/kWp/d), and deployment year. (b) Corresponding distributions of per-feature SHAP values (log 2025$/W) on predicted onshore wind installation cost for the same clusters and features, with wind power density replacing wind yield. Boxes span the interquartile range (IQR) with the central line marking the median, whiskers extend to 1.5 × IQR, and points beyond denote outliers. Clusters were obtained by k-means partitioning of the per-observation SHAP value matrix from the random forest installation cost model. Cluster 1 (red), Cluster 2 (blue), and Cluster 3 (green) correspond to early-period high-turbine-price, recent mid-scale low-turbine-price, and large-market mature-deployment country-year regimes, respectively.

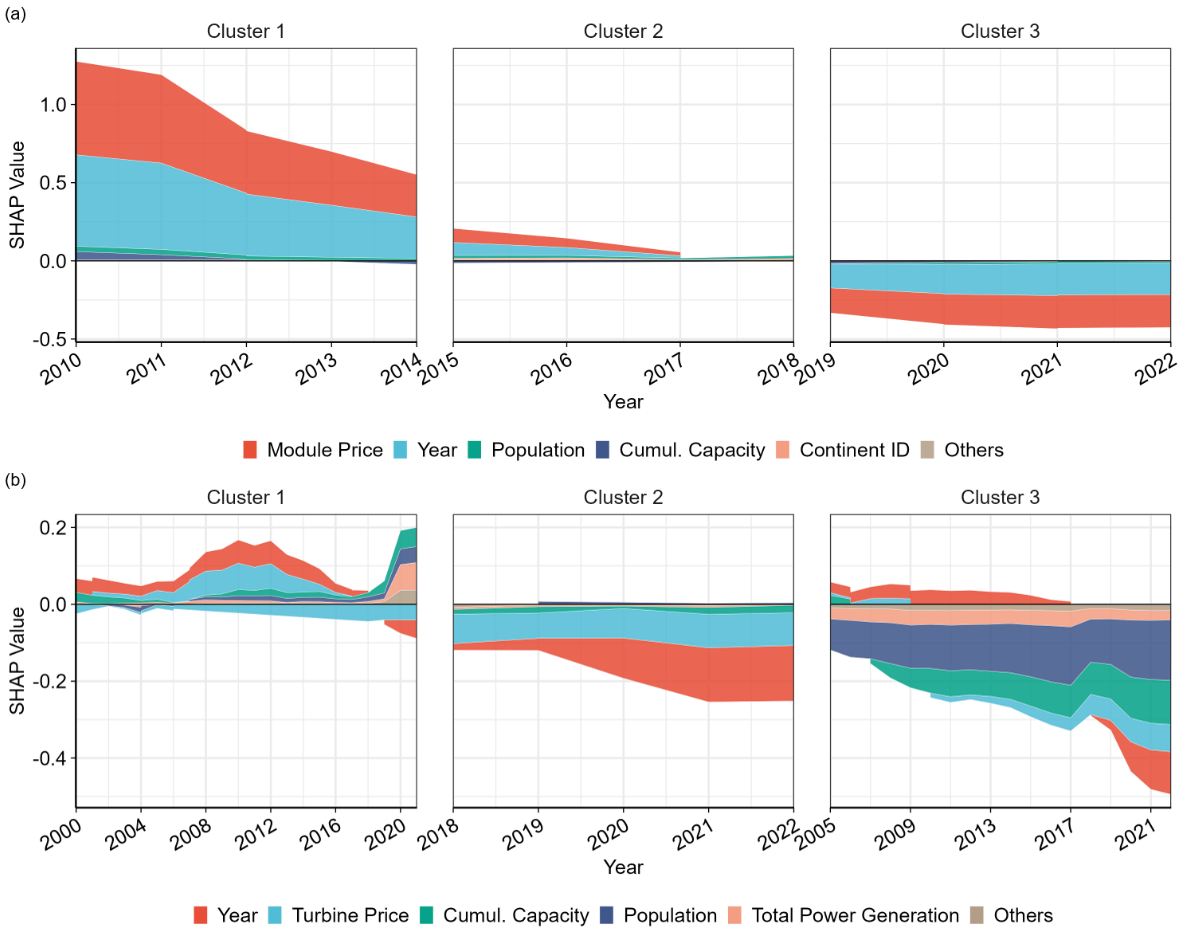


Fig. S10. Temporal evolution of cluster-wise SHAP contributions for solar PV and onshore wind installation cost models

(a) Year-resolved stacked SHAP value trajectories for the solar PV installation cost model across the three SHAP-defined clusters, with contributions from module price, deployment year, population, cumulative installed capacity, continent identifier, and aggregated remaining features (Others). **(b)** Corresponding year-resolved stacked SHAP value trajectories for the onshore wind installation cost model, with contributions from deployment year, turbine price, cumulative installed capacity, population, total power generation, and aggregated remaining features (Others). Positive and negative stacked areas denote upward and downward contributions to predicted log-transformed installation cost, respectively. Clusters were obtained by k-means partitioning of the per-observation SHAP value matrix from each random forest installation cost model, and correspond to early-period high-cost, mid-period transitional, and recent low-cost country-year regimes.

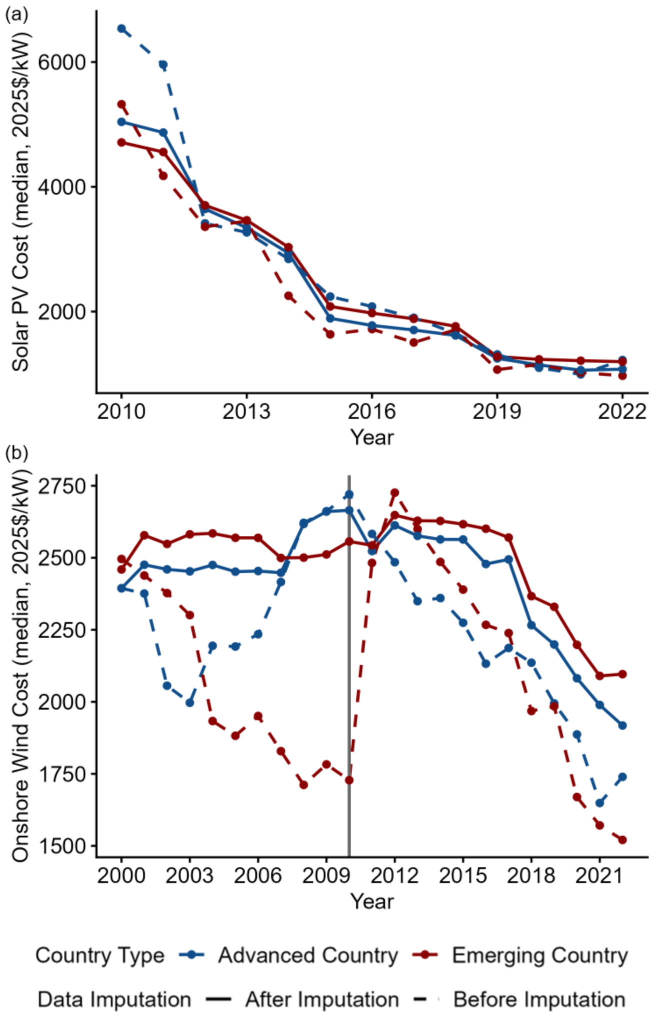


Fig. S11. Median installation cost trajectories before and after random forest imputation for solar PV and onshore wind

Random forest imputation preserves the long-term declining cost trajectory of solar PV while smoothing the high inter-annual volatility of pre-imputation onshore wind costs, particularly in emerging countries before 2010. **(a)** Annual median installation cost (2025$ kW^{-1}) of solar PV from 2010 to 2022, disaggregated by developed (blue) and emerging (red) countries, comparing observed values before imputation (dashed lines) with the completed series after random forest imputation (solid lines). **(b)** Corresponding annual median installation cost trajectories for onshore wind from 2000 to 2022 under the same country and imputation stratification, with the vertical grey line marking the 2010 reference year separating the volatile early-period emerging-country observations from the more densely reported recent period. Country classification follows the IMF developed versus emerging market taxonomy. Missing country-year cost observations were imputed using a random forest model trained on the available cost records together with the techno-economic and socioeconomic feature set described in the Methods.

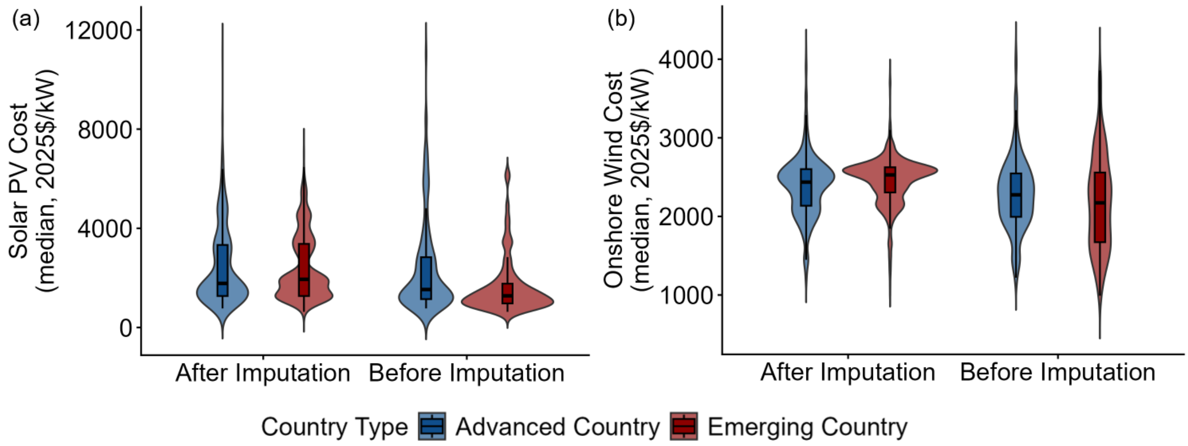


Fig. S12. Installation cost distributions before and after random forest imputation for solar PV and onshore wind

Random forest imputation raises the central tendency and narrows the lower tail of installation cost distributions for both solar PV and onshore wind, with the effect most pronounced for emerging countries. **(a)** Violin plots of country-year median solar PV installation cost (2025\$ kW^{-1}) before and after random forest imputation, disaggregated by developed (blue) and emerging (red) countries. **(b)** Corresponding violin plots of country-year median onshore wind installation cost under the same imputation and country stratification. Violin widths represent the kernel density of the cost distribution, embedded box plots span the interquartile range (IQR) with the central line marking the median, and whiskers extend to 1.5 × IQR. Country classification follows the IMF developed versus emerging market taxonomy. Missing country-year cost observations were imputed using a random forest model trained on available cost records together with the techno-economic and socioeconomic feature set described in the Methods.

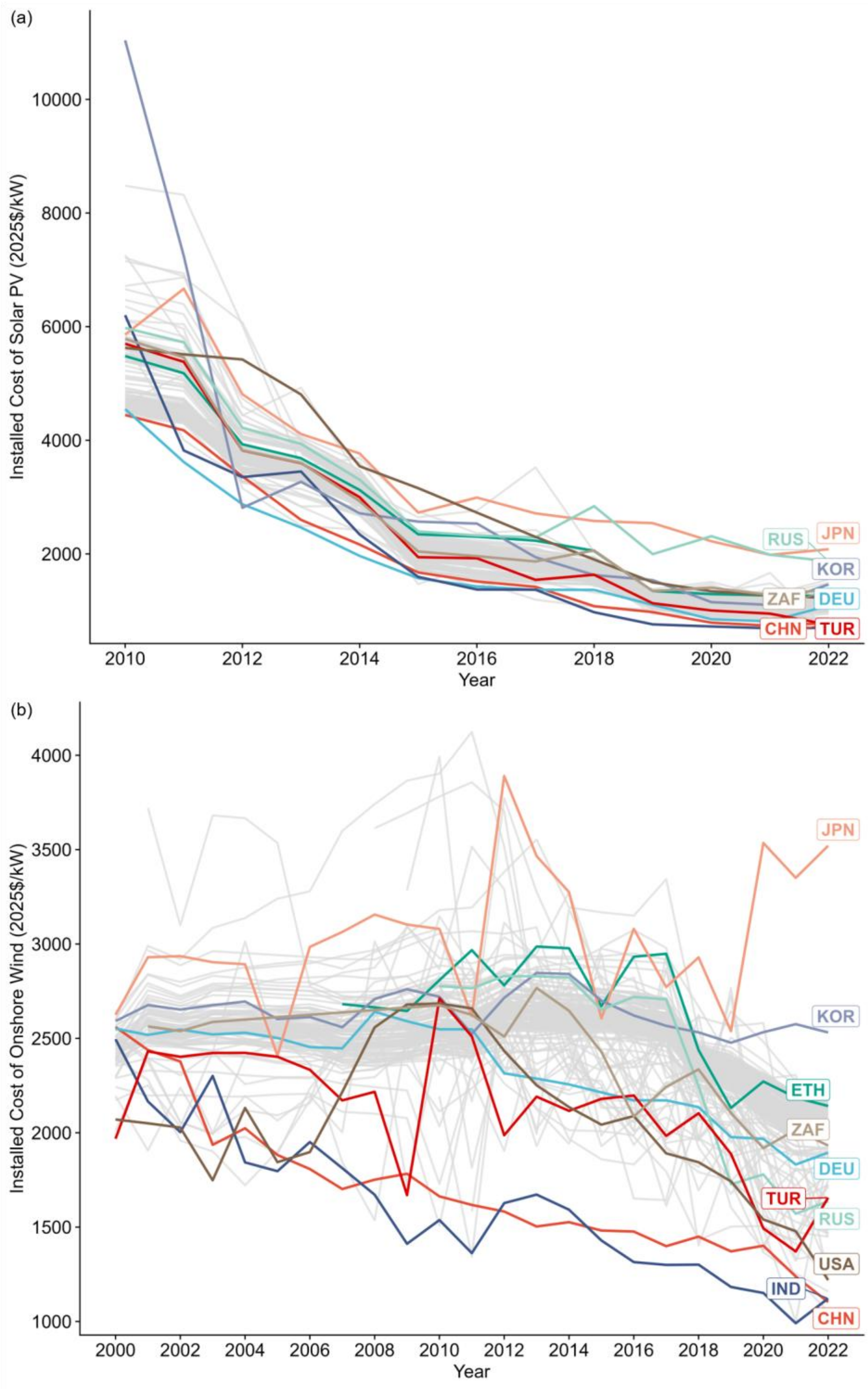


Fig. S13. Country-level installation cost trajectories of solar PV and onshore wind for selected major markets

Solar PV installation costs converged globally toward a narrow 1000-2000 \$ kW^{-1} band by 2022, whereas onshore wind trajectories diverged, with China, India, and the United States reaching the low-cost frontier below 1500 \$ kW^{-1} while Japan remained an outlier above 3500 \$ kW^{-1}. (a) Country-level trajectories of median solar PV installation cost (2025\$ kW^{-1}) from 2010 to 2022, with highlighted lines denoting selected major markets (CHN, IND, TUR, KOR, ZAF, RUS, JPN) and grey lines representing all remaining countries. (b) Corresponding country-level trajectories of median onshore wind installation cost from 2000 to 2022, with highlighted lines denoting CHN,

IND, USA, TUR, RUS, DEU, ZAF, ETH, KOR, and JPN. Country labels follow ISO-3 codes and are positioned at the 2022 endpoint of each highlighted trajectory. Country-year cost values were derived from the random forest imputed dataset described in the Methods.

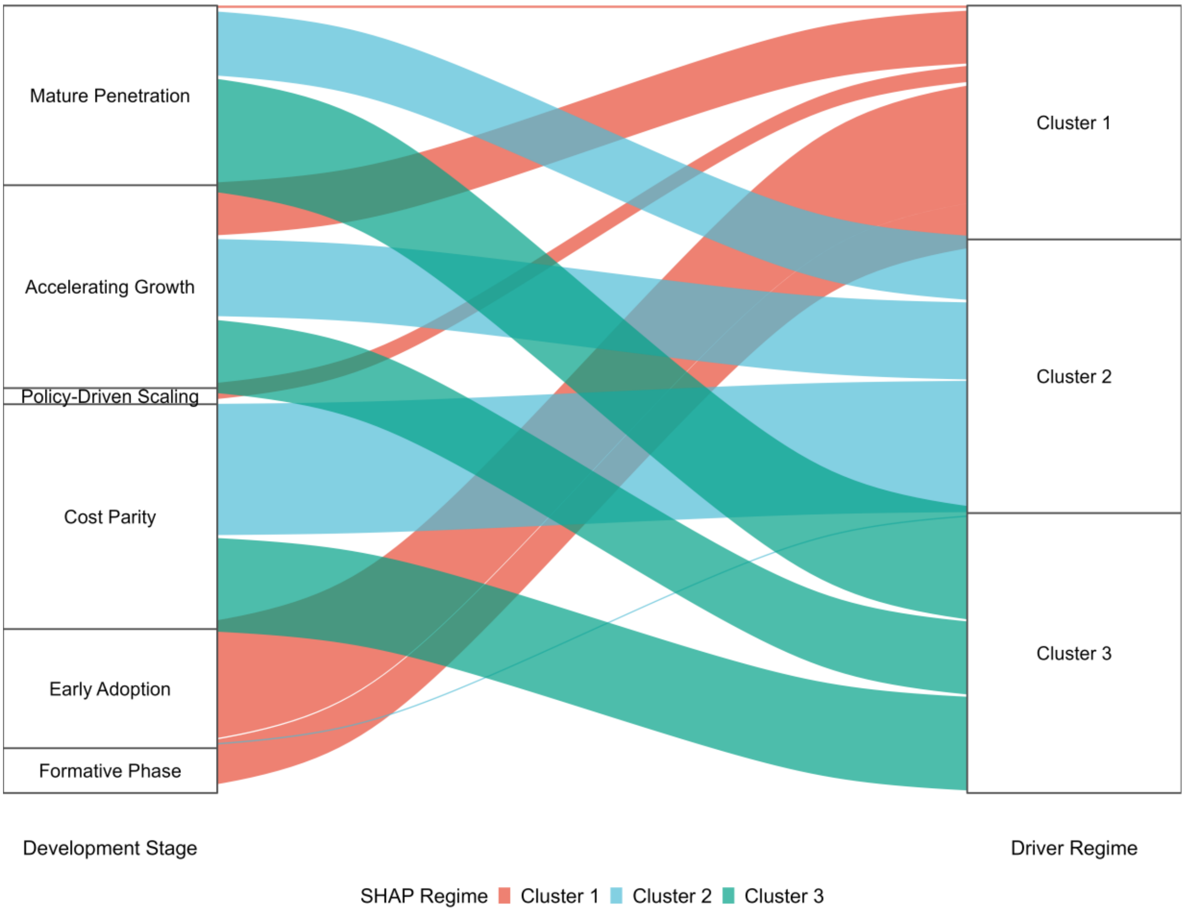


Fig. S14. Alluvial mapping between renewable deployment stages and SHAP-defined driver regimes for solar PV

Alluvial diagram linking six deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration) on the left to three SHAP-defined driver regimes (Cluster 1, Cluster 2, Cluster 3) on the right, where ribbon width is proportional to the number of country-year observations in each stage-to-cluster pairing. Deployment stages assigned were described in the Methods, and driver regimes were obtained by k-means partitioning of the per-observation SHAP value matrix from the random forest installation cost model. Ribbon colours denote the destination SHAP cluster (Cluster 1 red, Cluster 2 blue, Cluster 3 green).

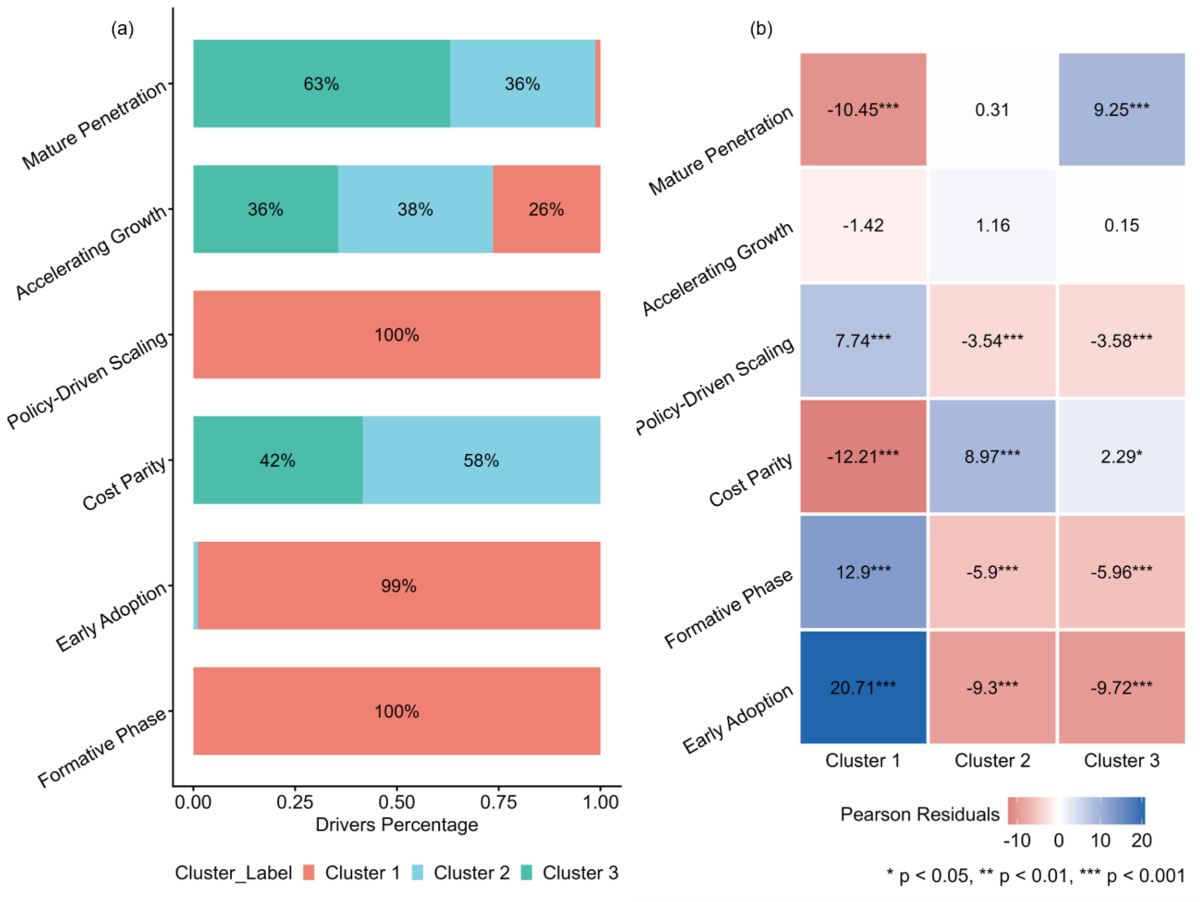


Fig. S15. Stage-wise driver regime composition and chi-square association for the solar PV installation cost model

(a) Stacked composition of the three SHAP-defined driver regimes (Cluster 1 red, Cluster 2 blue, Cluster 3 green) within each of the six solar PV deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration), with percentages labelled for bars exceeding 1%. **(b)** Pearson residuals from the chi-square test of independence between deployment stage and driver regime, where positive residuals (blue) indicate observed frequencies exceeding expected values under independence, negative residuals (red) indicate the reverse, and asterisks denote significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Deployment stages assigned were described in the Methods, and driver regimes were obtained by k-means partitioning of the per-observation SHAP value matrix from the random forest solar PV installation cost model.

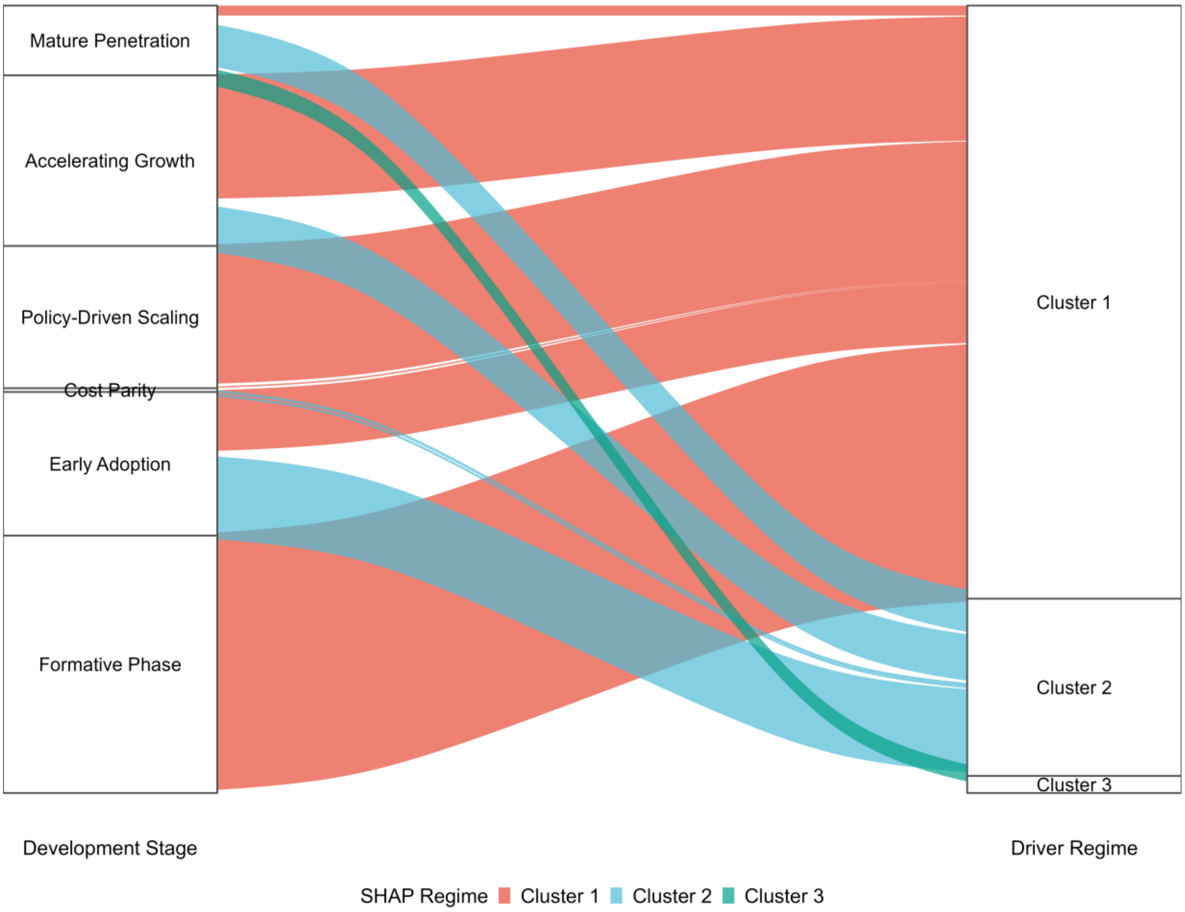


Fig. S16. Alluvial mapping between onshore wind deployment stages and SHAP-defined driver regimes

Alluvial diagram linking six onshore wind deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration) on the left to three SHAP-defined driver regimes (Cluster 1, Cluster 2, Cluster 3) on the right, where ribbon width is proportional to the number of country-year observations in each stage-to-cluster pairing. Deployment stages assigned were described in the Methods, and driver regimes were obtained by k-means partitioning of the per-observation SHAP value matrix from the random forest onshore wind installation cost model. Ribbon colours denote the destination SHAP cluster (Cluster 1 red, Cluster 2 blue, Cluster 3 green).

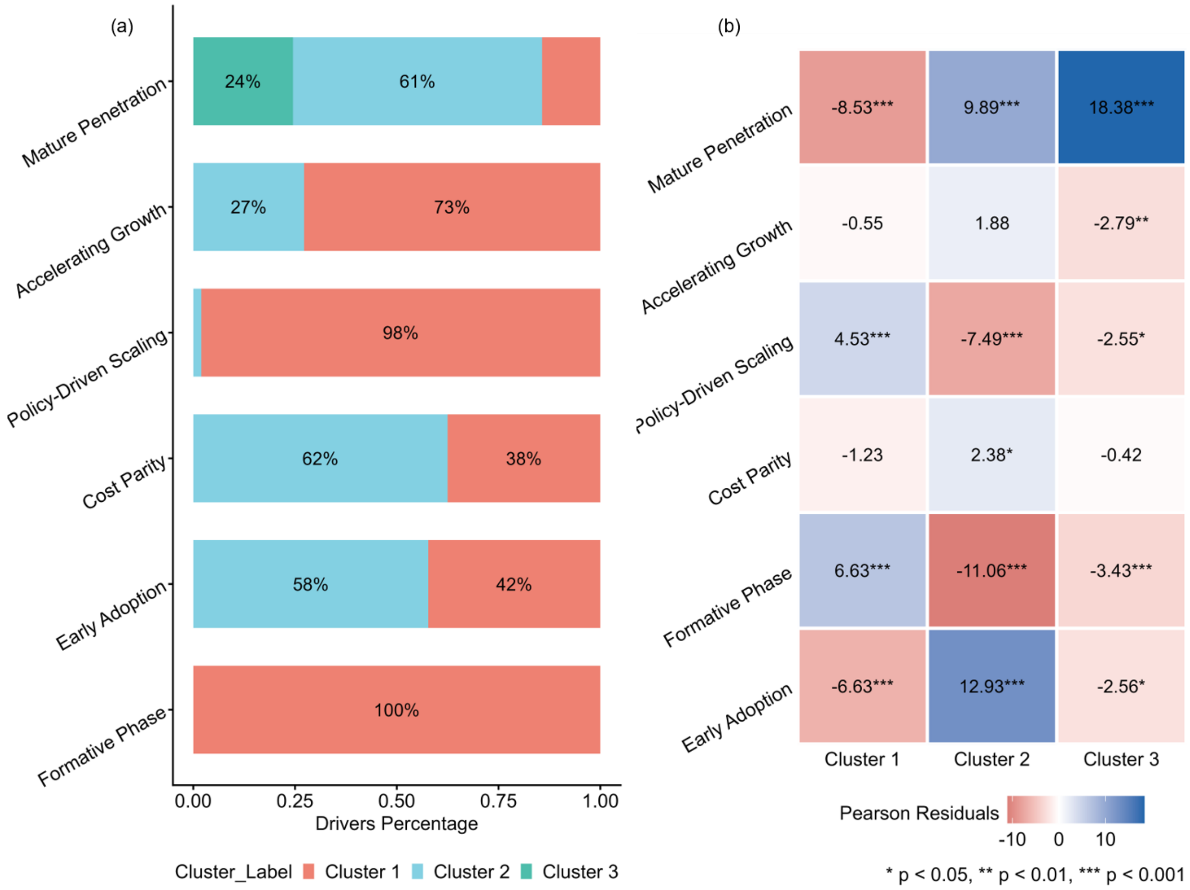


Fig. S17. Stage-wise driver regime composition and chi-square association for the onshore wind installation cost model

(**a**) Stacked composition of the three SHAP-defined driver regimes (Cluster 1 red, Cluster 2 blue, Cluster 3 green) within each of the six onshore wind deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration), with percentages labelled for bars exceeding 1%. (**b**) Pearson residuals from the chi-square test of independence between deployment stage and driver regime, where positive residuals (blue) indicate observed frequencies exceeding expected values under independence, negative residuals (red) indicate the reverse, and asterisks denote significance levels (*p<0.05, **p<0.01, ***p<0.001). Deployment stages assigned were described in the Methods, and driver regimes were obtained by k-means partitioning of the per-observation SHAP value matrix from the random forest onshore wind installation cost model.

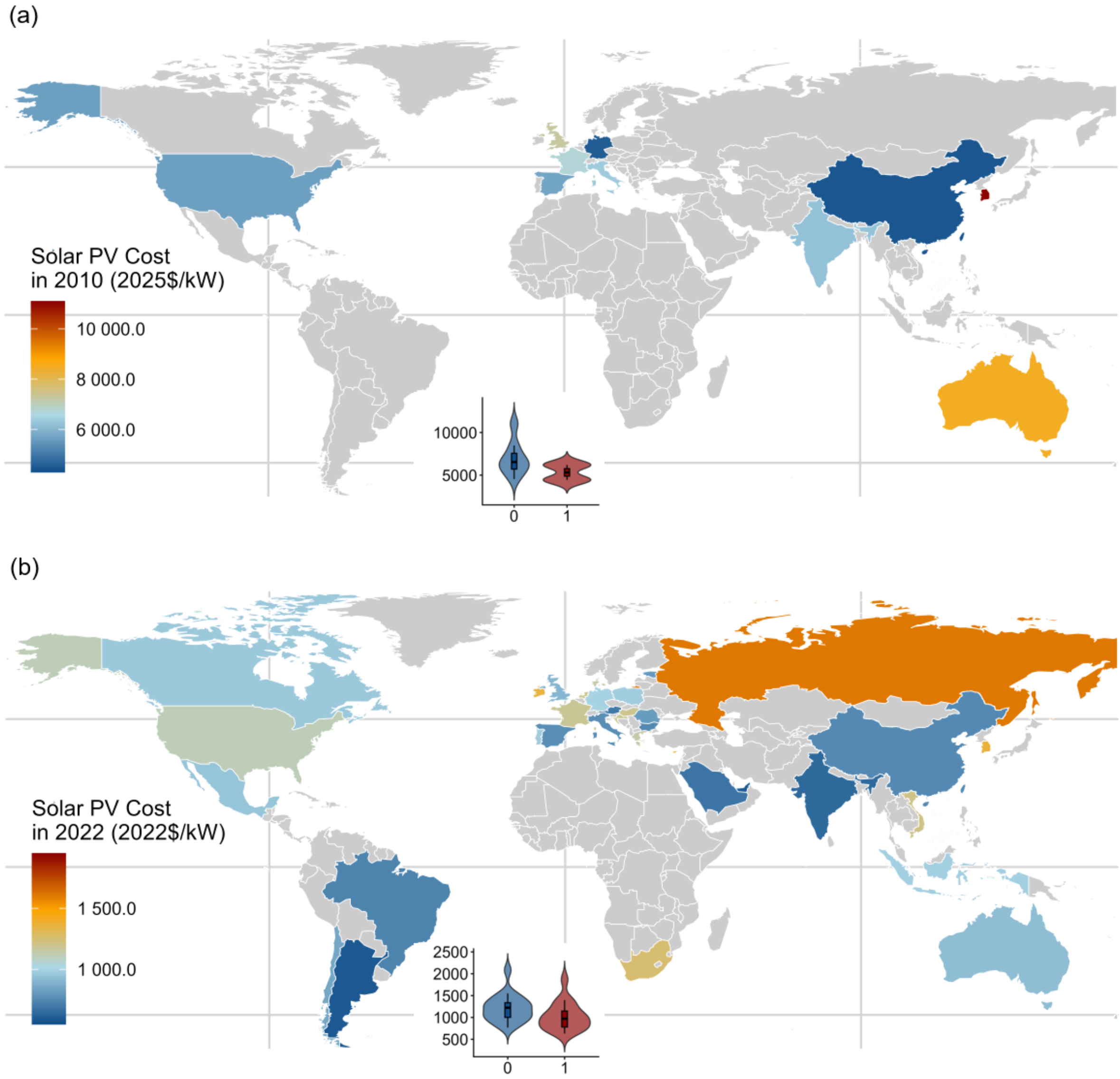


Fig. S18. Pre-imputation country-level solar PV installation costs in 2010 and 2022

Pre-imputation solar PV cost reporting expanded from sparse developed-economy coverage above 4000 $ kW^{-1} in 2010 to broader cross-continental coverage below 1500 $ kW^{-1} by 2022, while the cost gap between developed and emerging economies narrowed over the same period. (**a**) Country-level choropleth of observed solar PV installation cost (2025$ kW^{-1}) in 2010 before random forest imputation, with grey denoting countries without reported cost records, and the inset violin plot comparing the cost distributions of developed (0, blue) and emerging (1, red) economies with embedded box plots spanning the interquartile range and central lines marking the median. (**b**) Country-level choropleth and inset violin plot for observed solar PV installation cost in 2022 under the same plotting conventions and economy classification. Country classification follows the IMF developed versus emerging market taxonomy. Cost values represent raw country-year records from IRENA and national reporting sources prior to the random forest imputation described in the Methods.

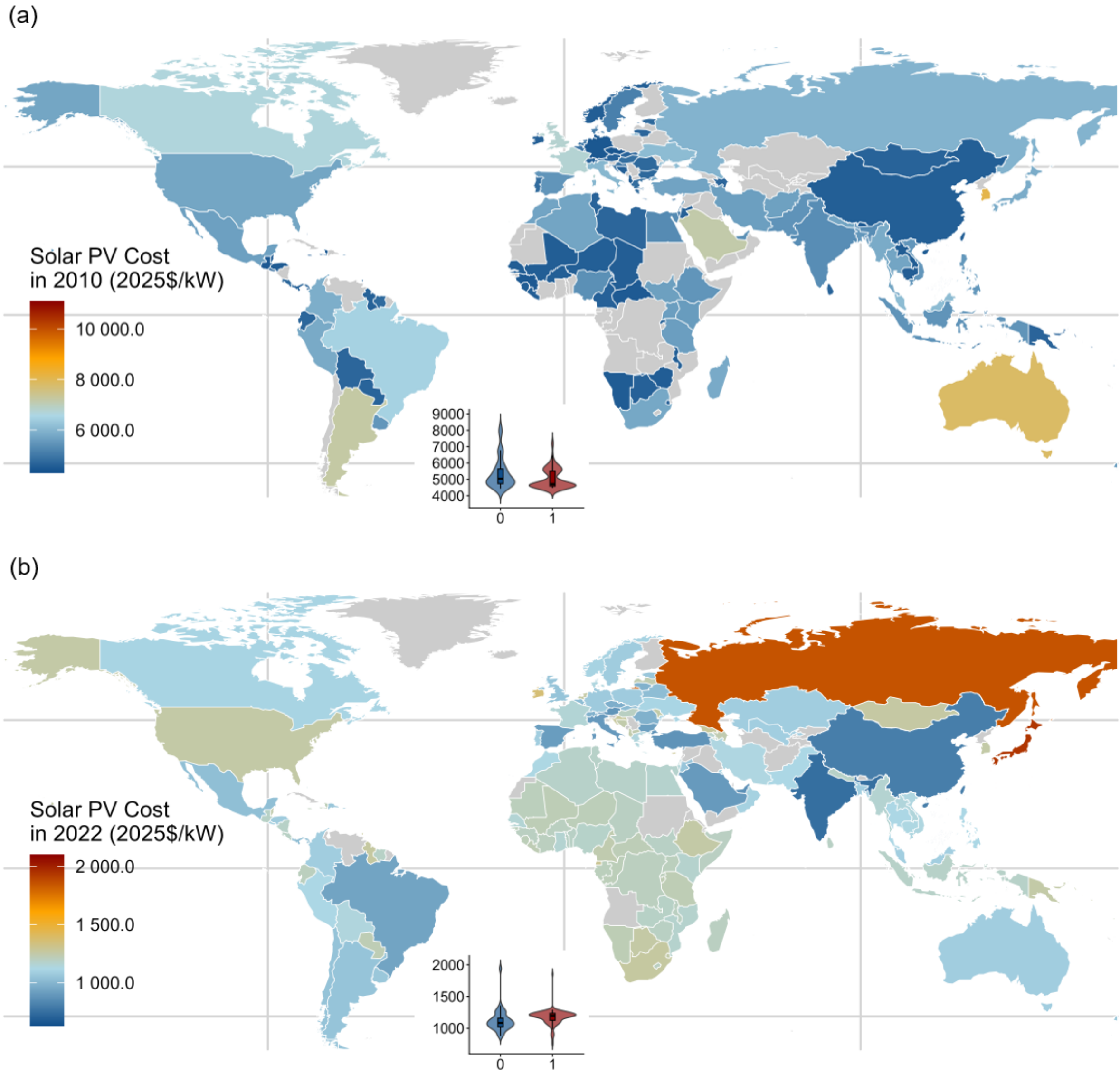


Fig. S19. Post-imputation country-level solar PV installation costs in 2010 and 2022

Random forest imputation extends solar PV cost coverage to the full global country set for both 2010 and 2022, revealing a uniform downward shift from a 4000-8000 \$ kW^{-1} band in 2010 to a narrower 500-1500 \$ kW^{-1} band in 2022, with Russia and Japan emerging as persistent high-cost outliers by 2022. (**a**) Country-level choropleth of imputed solar PV installation cost (2025\$ kW^{-1}) in 2010, with grey denoting countries excluded from the modelling domain, and the inset violin plot comparing the cost distributions of developed (0, blue) and emerging (1, red) economies with embedded box plots spanning the interquartile range and central lines marking the median. (**b**) Country-level choropleth and inset violin plot for imputed solar PV installation cost in 2022. Country classification follows the IMF developed versus emerging market taxonomy. Cost values represent country-year estimates after random forest imputation trained on observed cost records together with the techno-economic and socioeconomic feature set described in the Methods.

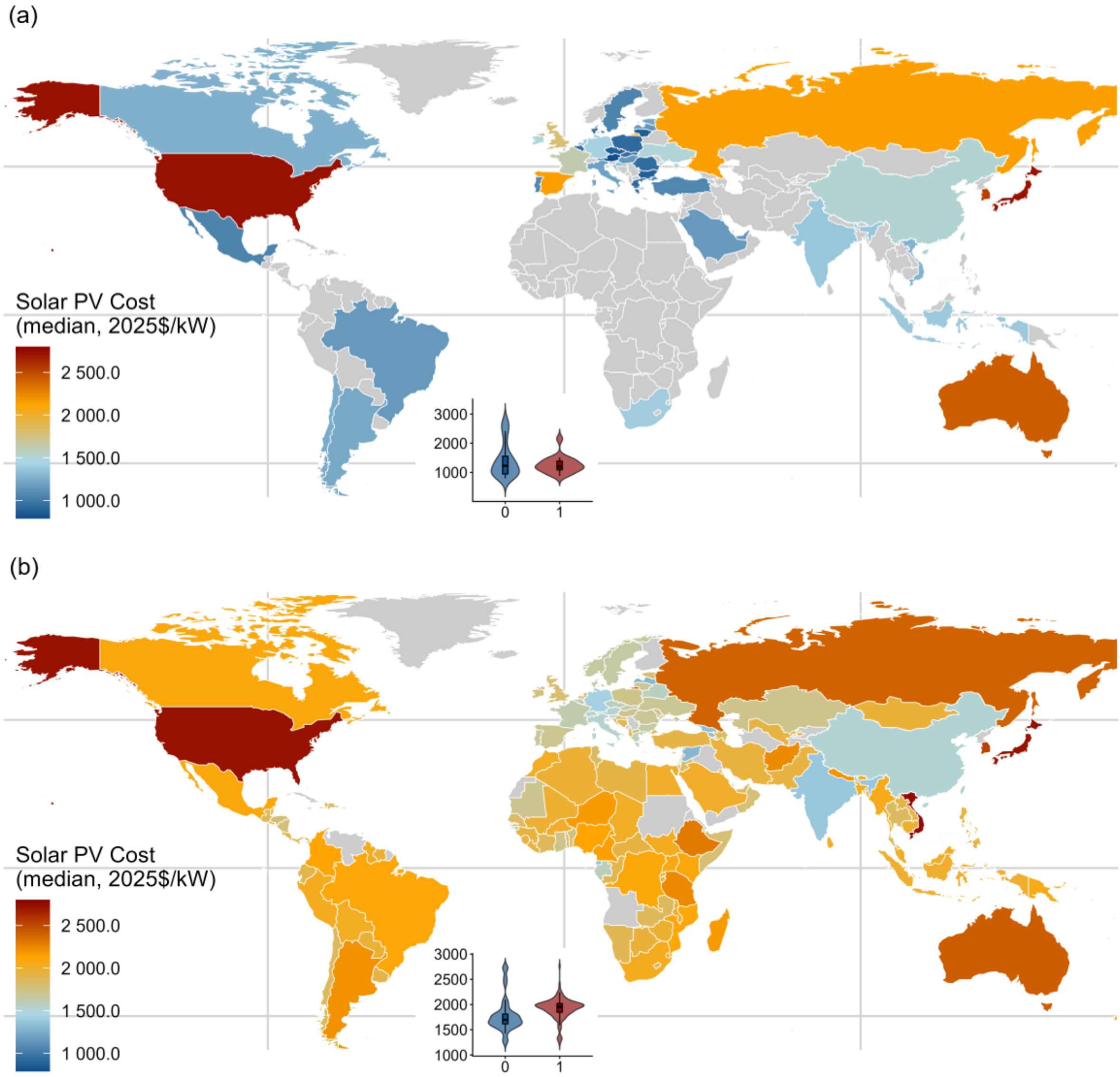


Fig. S20. Country-level median solar PV installation costs before and after imputation

Random forest imputation extends median solar PV cost coverage from a limited subset of reporting countries to the full global modelling domain, while shifting the cross-country distribution upward from a 1000-1500 $ kW^{-1} centre of mass to a 1500-2000 $ kW^{-1} band, with the United States persisting as the highest-cost major market under both datasets. (**a**) Country-level choropleth of observed median solar PV installation cost (2025$ kW^{-1}) before random forest imputation, with grey denoting countries without reported cost records, and the inset violin plot comparing the cost distributions of developed (0, blue) and emerging (1, red) economies with embedded box plots spanning the interquartile range and central lines marking the median. (**b**) Country-level choropleth and inset violin plot of median solar PV installation cost after random forest imputation, under the same plotting conventions and economy classification. Country medians were computed across all country-year observations in the respective dataset. Country classification follows the IMF developed versus emerging market taxonomy. Imputed values were generated by a random forest model trained on observed cost records together with the techno-economic and socioeconomic feature set described in the Methods.

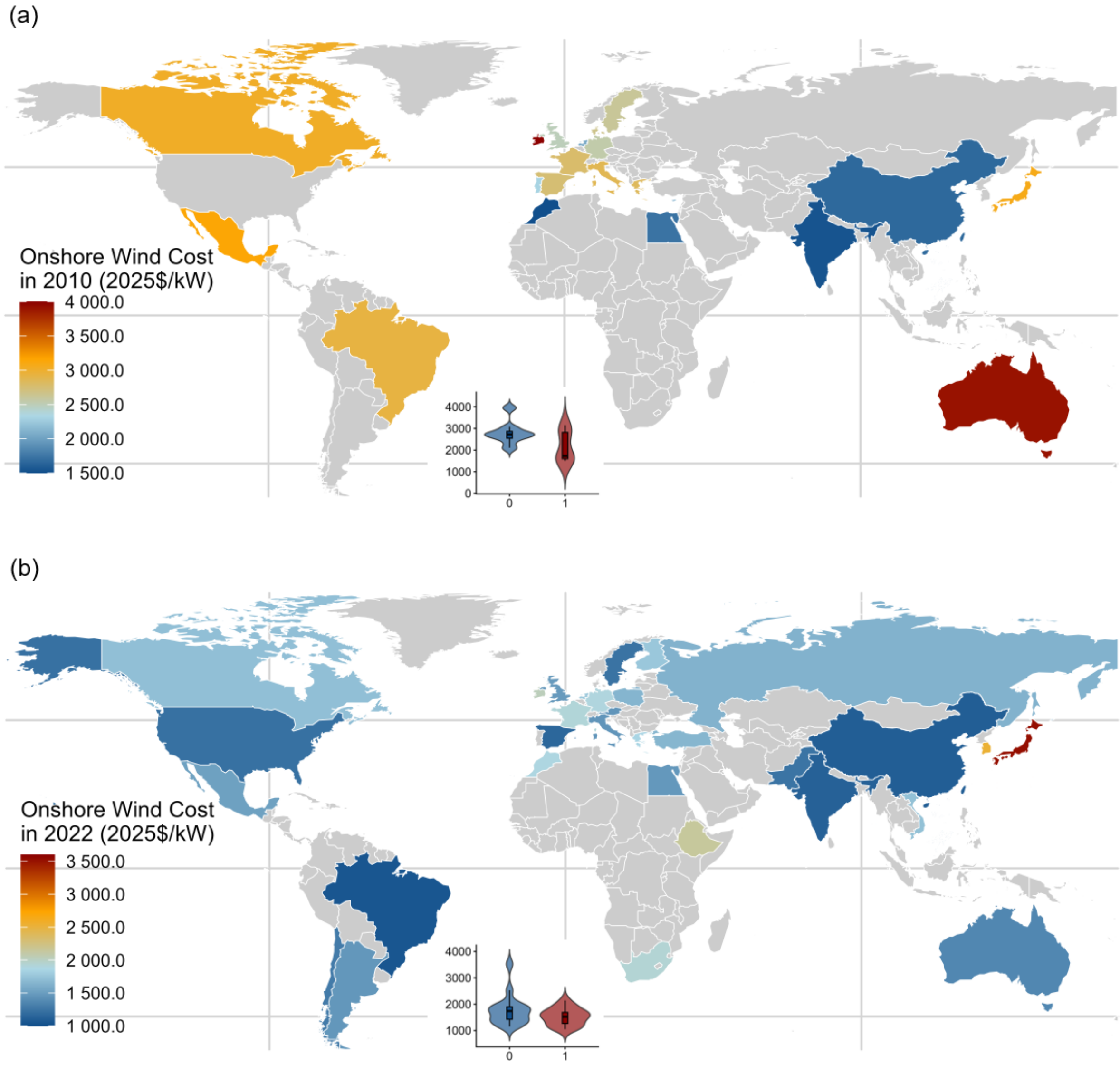
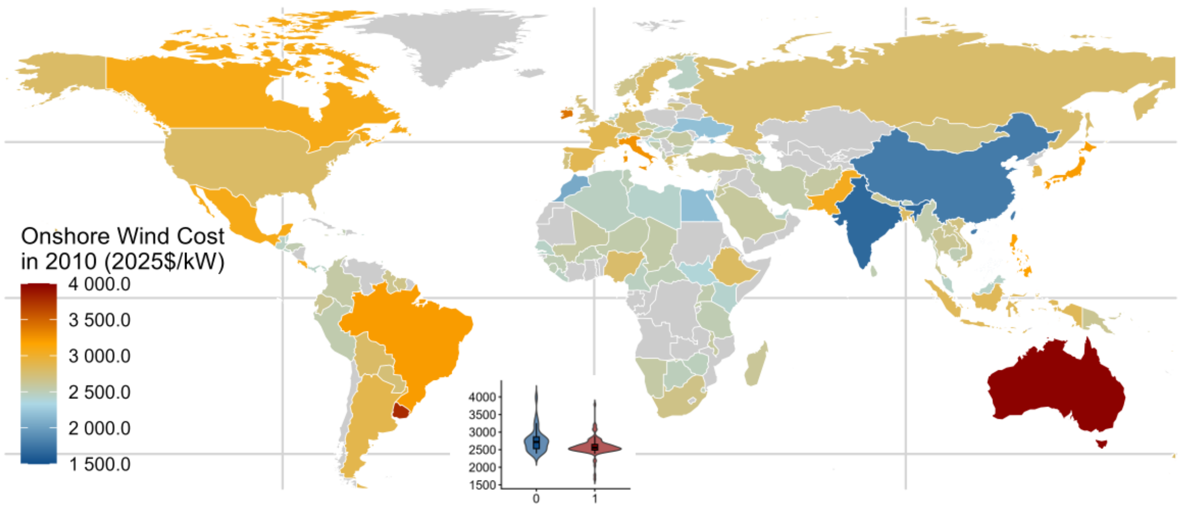


Fig. S21. Pre-imputation country-level onshore wind installation costs in 2010 and 2022

Pre-imputation onshore wind cost reporting expanded from sparse country coverage in 2010, with Australia exceeding 3500 \$ kW⁻¹ and China and India below 2000 \$ kW⁻¹, to broader cross-continental coverage by 2022 under a compressed 1000-2,000 \$ kW⁻¹ band, while Japan emerged as the sole persistent high-cost outlier above 3000 \$ kW⁻¹. (**a**) Country-level choropleth of observed onshore wind installation cost (2025\$ kW⁻¹) in 2010 before random forest imputation, with grey denoting countries without reported cost records, and the inset violin plot comparing the cost distributions of developed (0, blue) and emerging (1, red) economies with embedded box plots spanning the interquartile range and central lines marking the median. (**b**) Country-level choropleth and inset violin plot for observed onshore wind installation cost in 2022. Country classification follows the IMF developed versus emerging market definitions.

(a)



(b)

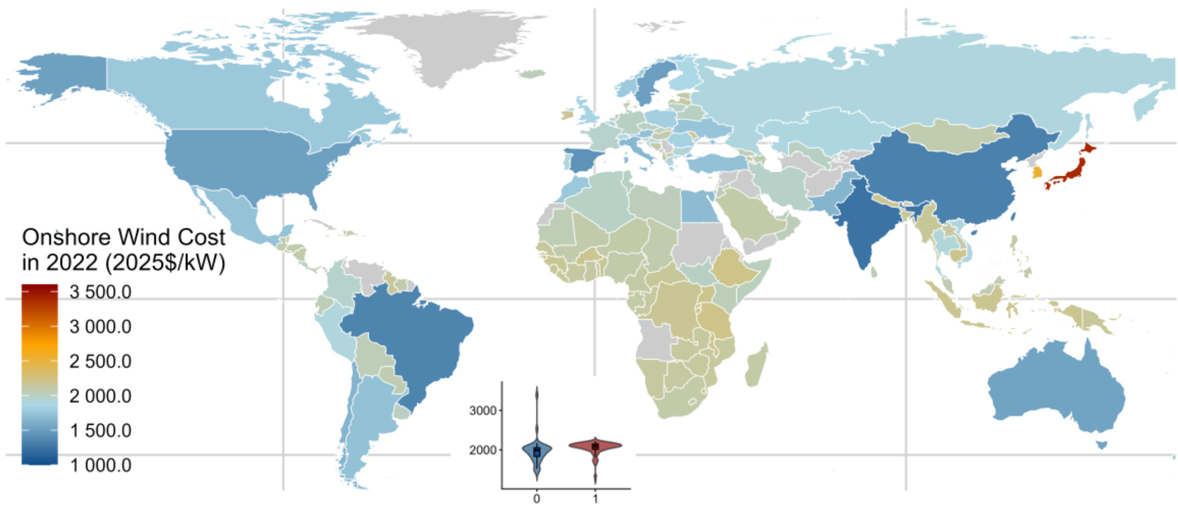


Fig. S22. Post-imputation country-level onshore wind installation costs in 2010 and 2022
Random forest imputation reveals a global onshore wind cost decline from a 2000-2500 $ kW^{-1} centre of mass in 2010 to a 1500-2000 $ kW^{-1} band by 2022, alongside a compression of the cross-country spread, with Japan emerging as the sole persistent high-cost outlier above 3000 $ kW^{-1}. (**a**) Country-level choropleth of imputed onshore wind installation cost (2025$ kW^{-1}) in 2010, with grey denoting countries excluded from the modelling domain, and the inset violin plot comparing the cost distributions of developed (0, blue) and emerging (1, red) economies with embedded box plots spanning the interquartile range and central lines marking the median. (**b**) Country-level choropleth and inset violin plot for imputed onshore wind installation cost in 2022. Country classification follows the IMF developed versus emerging market taxonomy. Cost values represent country-year estimates after random forest imputation trained on observed cost records together with the techno-economic and socioeconomic feature set described in the Methods.

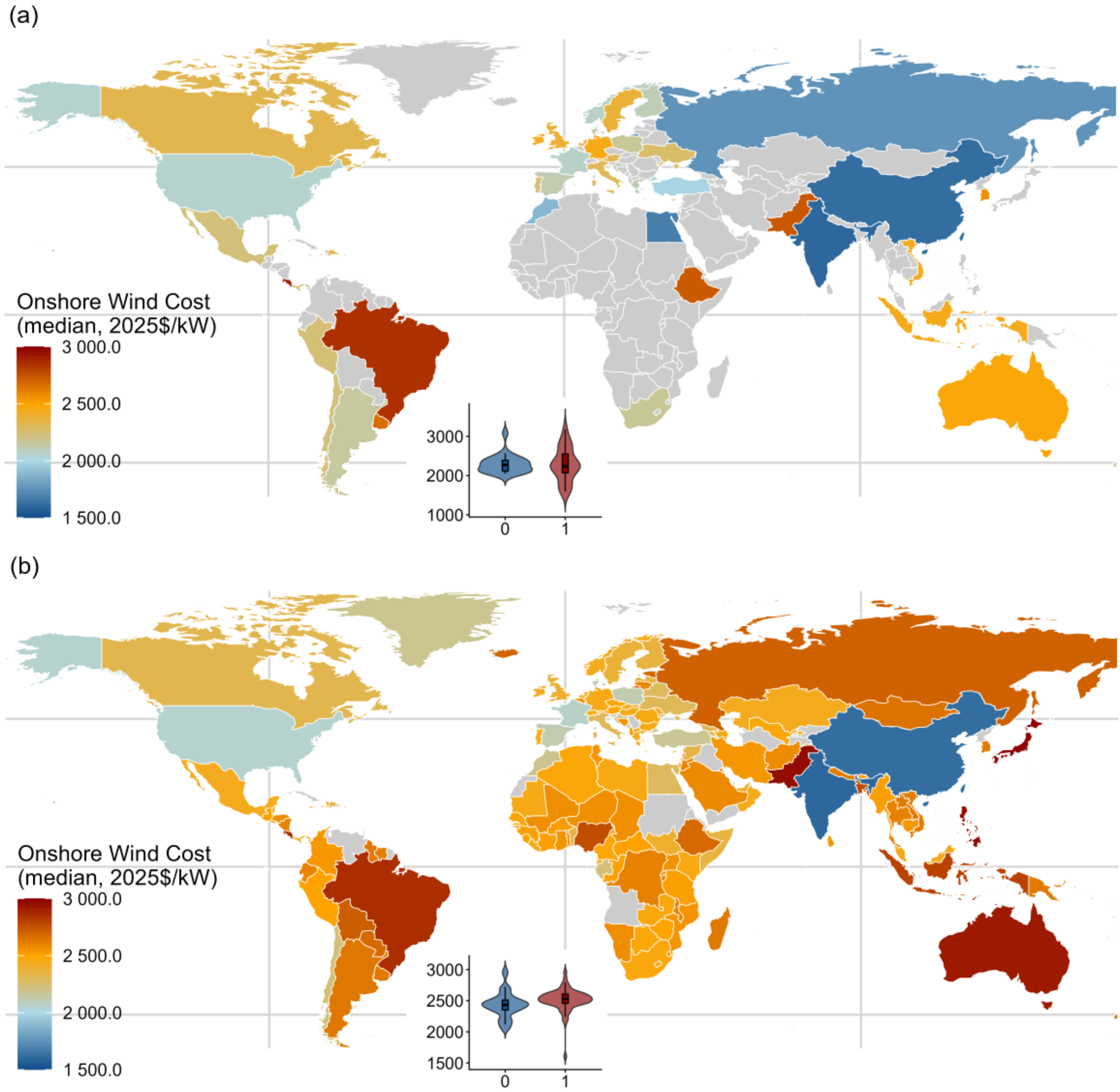


Fig. S23. Country-level median onshore wind installation costs before and after random forest imputation

Random forest imputation extends median onshore wind cost coverage from a limited subset of reporting countries to the full global modelling domain, shifting the cross-country distribution upward from a 2000-2400 $ kW^{-1} centre of mass to a 2200-2600 $ kW^{-1} band, while China and India remain at the low-cost frontier while Japan and Brazil persists as the high-cost major market under both datasets. (**a**) Country-level choropleth of observed median onshore wind installation cost (2025$ kW^{-1}) before random forest imputation, with grey denoting countries without reported cost records, and the inset violin plot comparing the cost distributions of developed (0, blue) and emerging (1, red) economies with embedded box plots spanning the interquartile range and central lines marking the median. (**b**) Country-level choropleth and inset violin plot of median onshore wind installation cost after random forest imputation. Country medians were computed across all country-year observations in the respective dataset. Country classification follows the IMF developed versus emerging market taxonomy. Imputed values were generated by a random forest model trained on observed cost records together with the techno-economic and socioeconomic feature set described in the Methods.

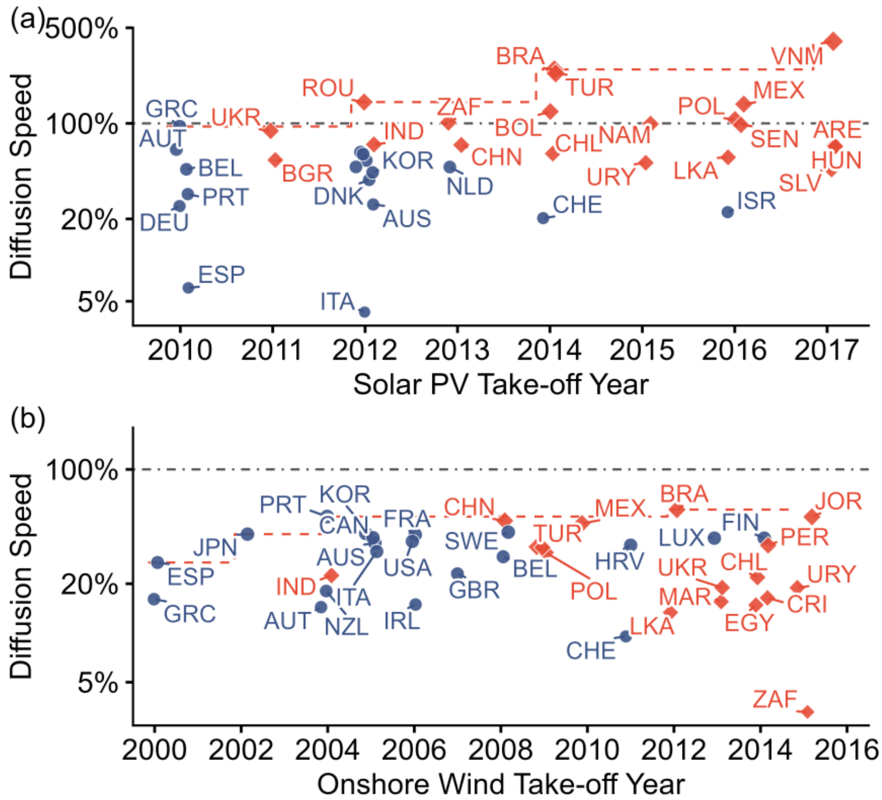


Fig. S24. Country-level diffusion speed versus technology take-off year for solar PV and onshore wind

Country-level diffusion speed showed no monotonic relationship with take-off year for either solar PV or onshore wind, but economy type stratified the distribution, with emerging economies spanning a wider range that extended above the 100% yr^{-1} threshold while developed economies concentrated below 50% yr^{-1} across all take-off cohorts. (**a**) Country-level diffusion speed (% yr^{-1}, log scale) of solar PV plotted against national take-off year from 2012 to 2019, with developed economies (blue circles) and emerging economies (red diamonds) labelled by ISO-3 codes, and the horizontal dash-dotted line marking the 100% reference threshold. (**b**) Country-level diffusion speed and take-off year for onshore wind from 2000 to 2016. Take-off year and diffusion speed were defined in the Methods. Country classification follows the IMF developed versus emerging market taxonomy.

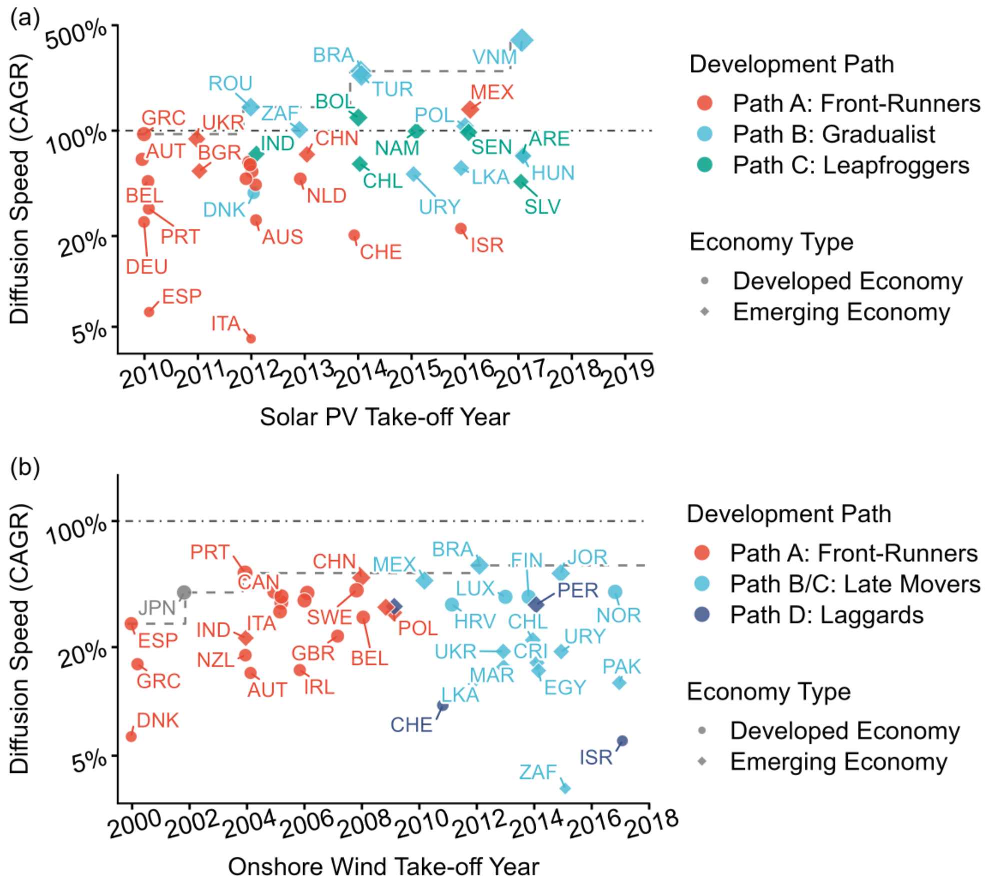
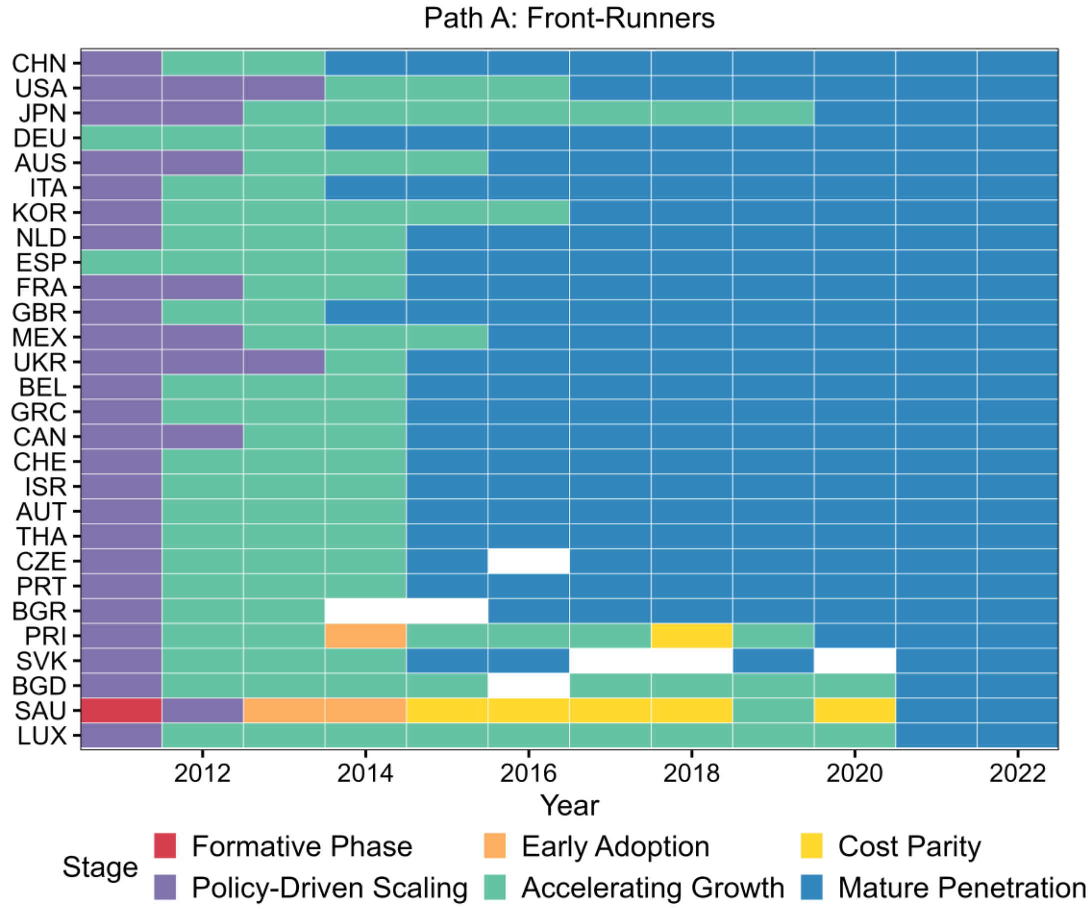
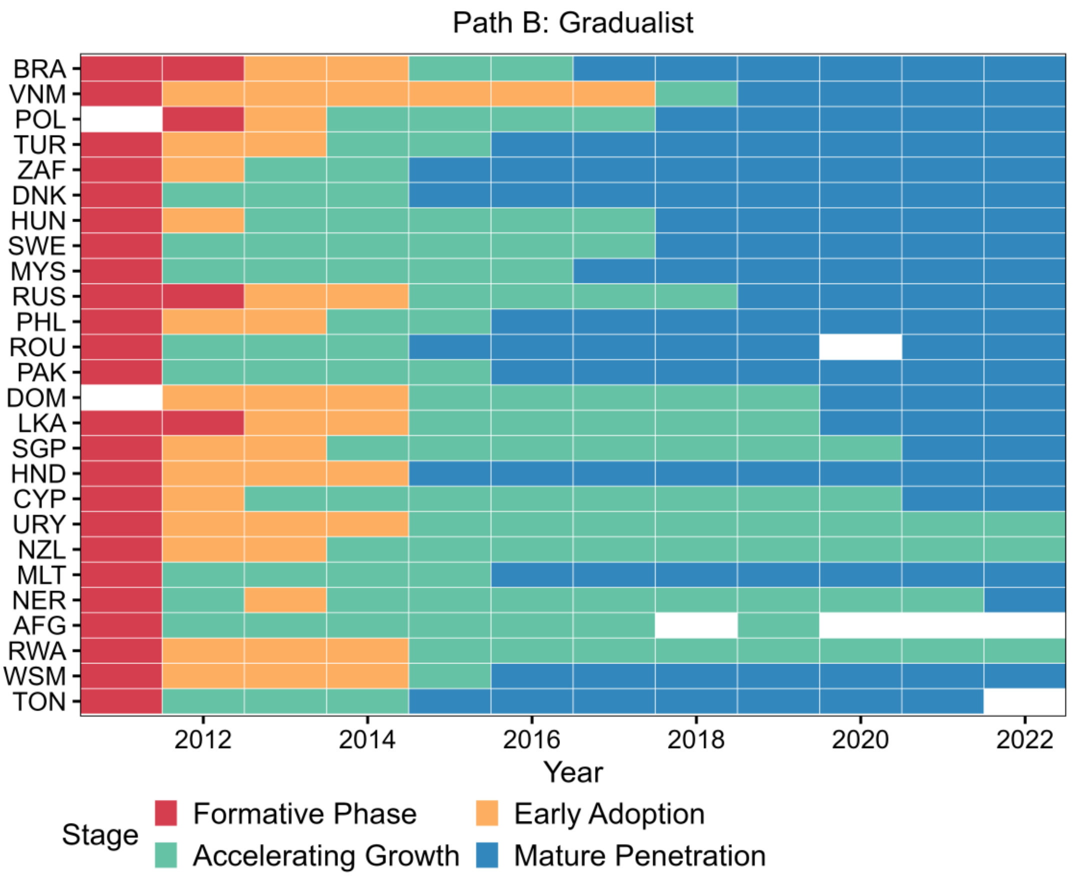
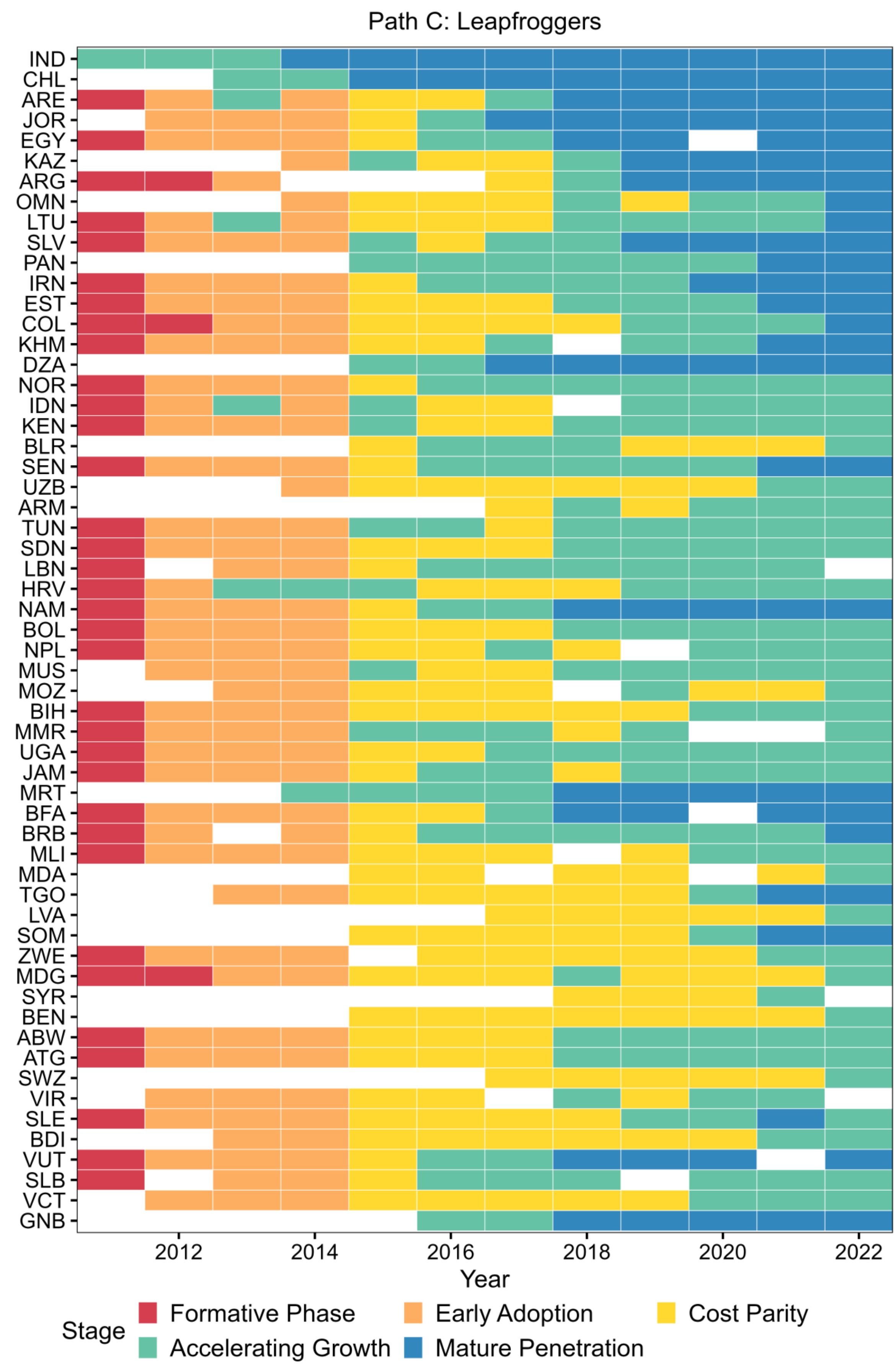


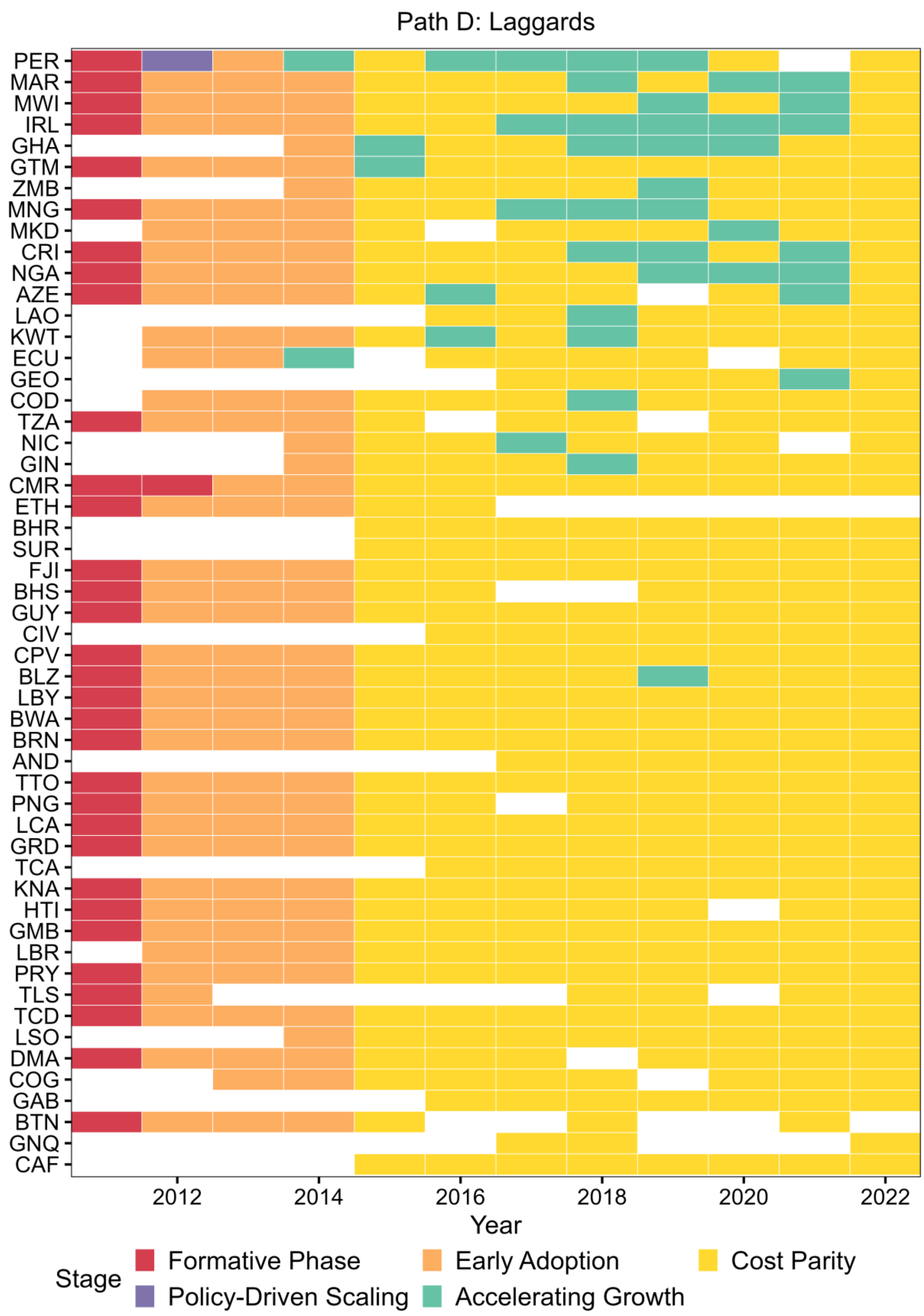
Fig. S25. Country-level diffusion speed and take-off year stratified by development path for solar PV and onshore wind

Development-path classification resolved the heterogeneity in country-level diffusion speed, with solar PV Leapfroggers (Path C) reaching triple-digit CAGR despite late or early take-off, Gradualists (Path B) concentrating above 100% yr^{-1} across mid-period take-off years, and Front-Runners (Path A) clustering below 50% yr^{-1}, while onshore wind Late Movers (Path B/C) spanned the widest range and Laggards (Path D) remained below 10% yr^{-1}. (**a**) Country-level diffusion speed (compound annual growth rate, % yr^{-1}, log scale) of solar PV plotted against national take-off year from 2011 to 2019, with markers coloured by development path (Path A Front-Runners red, Path B Gradualists light blue, Path C Leapfroggers green) and shaped by economy type (developed circles, emerging diamonds), countries labelled by ISO-3 codes, and the horizontal dash-dotted line marking the 100% yr^{-1} reference threshold. (**b**) Country-level diffusion speed and take-off year for onshore wind from 2000 to 2018, with development paths categorised as Path A Front-Runners (red), Path B/C Late Movers (light blue), and Path D Laggards (dark blue). Take-off year, diffusion speed and development paths were described in the Methods. Country classification follows the IMF developed versus emerging market taxonomy.


Path A: Front-Runners
CHN
USA
JPN
DEU
AUS
ITA
KOR
NLD
ESP
FRA
GBR
MEX
UKR
BEL
GRC
CAN
CHE
ISR
AUT
THA
CZE
PRT
BGR
PRI
SVK
BGD
SAU
LUX
2012
2014
2016
2018
2020
2022
Year
Stage
Formative Phase
Early Adoption
Cost Parity
Policy-Driven Scaling
Accelerating Growth
Mature Penetration


Path B: Gradualist
BRA
VNM
POL
TUR
ZAF
DNK
HUN
SWE
MYS
RUS
PHL
ROU
PAK
DOM
LKA
SGP
HND
CYP
URY
NZL
MLT
NER
AFG
RWA
WSM
TON
2012
2014
2016
2018
2020
2022
Year
Stage
Formative Phase
Early Adoption
Accelerating Growth
Mature Penetration


Path C: Leapfroggers
IND
CHL
ARE
JOR
EGY
KAZ
ARG
OMN
LTU
SLV
PAN
IRN
EST
COL
KHM
DZA
NOR
IDN
KEN
BLR
SEN
UZB
ARM
TUN
SDN
LBN
HRV
NAM
BOL
NPL
MUS
MOZ
BIH
MMR
UGA
JAM
MRT
BFA
BRB
MLI
MDA
TGO
LVA
SOM
ZWE
MDG
SYR
BEN
ABW
ATG
SWZ
VIR
SLE
BDI
VUT
SLB
VCT
GNB
2012
2014
2016
2018
2020
2022
Year
Stage
Formative Phase
Early Adoption
Cost Parity
Accelerating Growth
Mature Penetration


Path D: Laggards
PER
MAR
MWI
IRL
GHA
GTM
ZMB
MNG
MKD
CRI
NGA
AZE
LAO
KWT
ECU
GEO
COD
TZA
NIC
GIN
CMR
ETH
BHR
SUR
FJI
BHS
GUY
CIV
CPV
BLZ
LBY
BWA
BRN
AND
TTO
PNG
LCA
GRD
TCA
KNA
HTI
GMB
LBR
PRY
TLS
TCD
LSO
DMA
COG
GAB
BTN
GNQ
CAF
2012
2014
2016
2018
2020
2022
Year
Stage
Formative Phase
Early Adoption
Cost Parity
Policy-Driven Scaling
Accelerating Growth

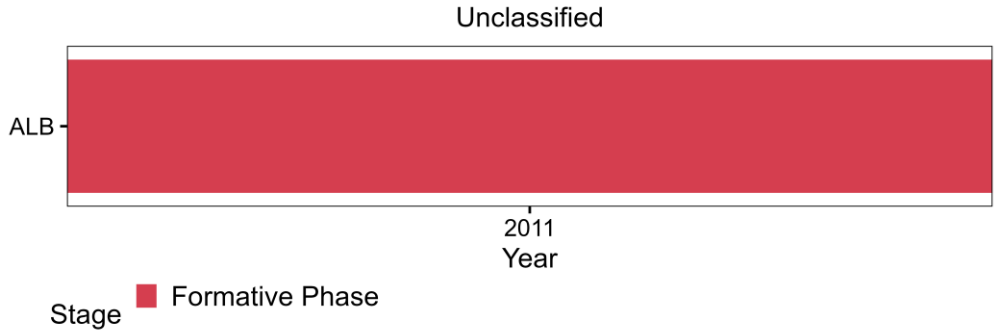
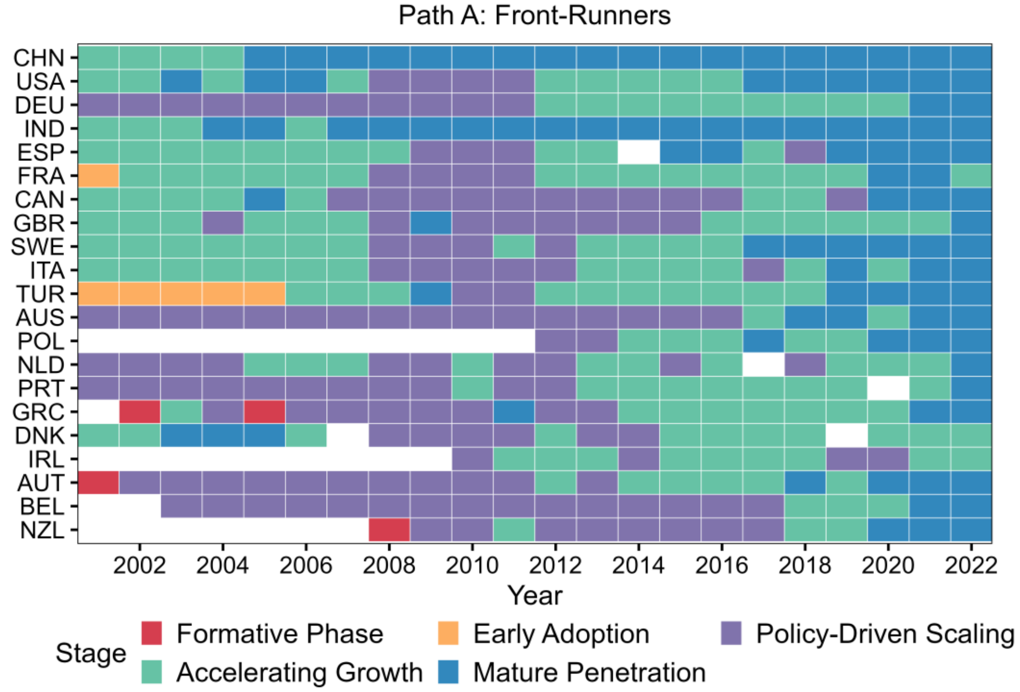
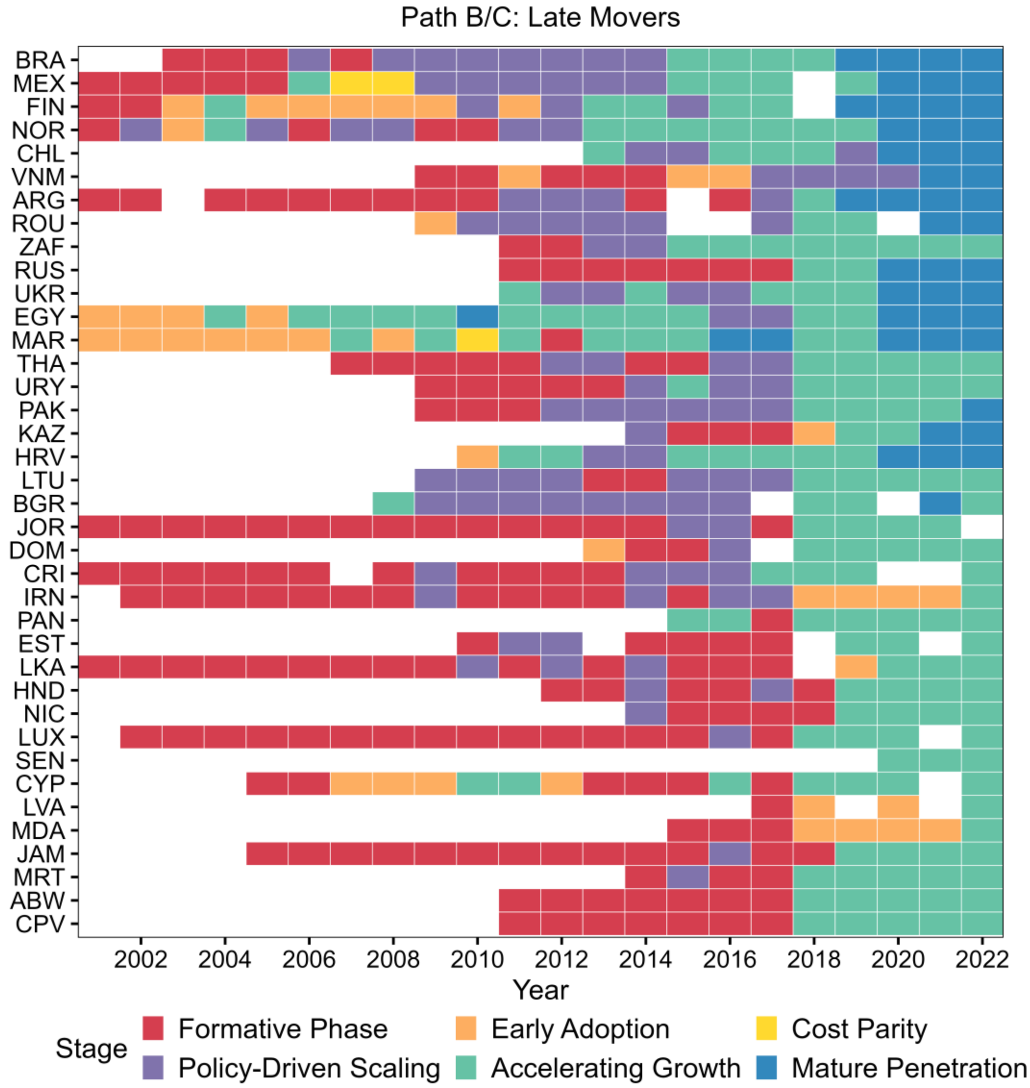


Fig. S26. Country-level solar PV deployment stage trajectories by development path from 2010 to 2022

(**Path A: Front-Runners**) Country-year deployment stage trajectories for Path A Front-Runners, with stages colour-coded as policy-driven scaling (purple), accelerating growth (green), mature penetration (blue), early adoption (orange), and cost parity (yellow), and countries labelled by ISO-3 codes. (**Path B: Gradualists**) Corresponding trajectories for Path B Gradualists, with take-off year occurring after 2010. (**Path C: Leapfroggers**) Trajectories for Path C Leapfroggers under the same stage colour coding. (**Path D: Laggards**) Trajectories for Path D Laggards under the same colour coding. (**Unclassified**) Trajectory for the unclassified country (ALB) restricted to the formative phase. White cells denote country-year observations excluded from the dataset. Deployment stages were described in the Methods.


Path A: Front-Runners
CHN
USA
DEU
IND
ESP
FRA
CAN
GBR
SWE
ITA
TUR
AUS
POL
NLD
PRT
GRC
DNK
IRL
AUT
BEL
NZL
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
Year
Stage
Formative Phase
Early Adoption
Policy-Driven Scaling
Accelerating Growth
Mature Penetration


Path B/C: Late Movers
BRA
MEX
FIN
NOR
CHL
VNM
ARG
ROU
ZAF
RUS
UKR
EGY
MAR
THA
URY
PAK
KAZ
HRV
LTU
BGR
JOR
DOM
CRI
IRN
PAN
EST
LKA
HND
NIC
LUX
SEN
CYP
LVA
MDA
JAM
MRT
ABW
CPV
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
Year
Stage
Formative Phase
Early Adoption
Cost Parity
Policy-Driven Scaling
Accelerating Growth
Mature Penetration


Path D: Laggards
PHL
KEN
PER
CZE
HUN
ETH
TUN
MNG
IDN
BIH
BOL
BLR
GTM
PRI
CHE
AZE
SLV
OMN
MKD
GEO
ISR
ECU
COL
KWT
MUS
DZA
FJI
NAM
SVK
VUT
SOM
SAU
LBN
ISL
ARM
BGD
TZA
ARE
TON
GMB
TCD
UZB
BHR
SYR
BTN
WSM
AFG
BHS
KHM
DMA
NPL
MDG
GUY
SGP
MLT
GRD
GRL
HTI
PRY
GHA
BLZ
TTO
MMR
2002
2004
2006
2008
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2022
Year
Stage
Formative Phase
Early Adoption
Cost Parity
Policy-Driven Scaling
Accelerating Growth

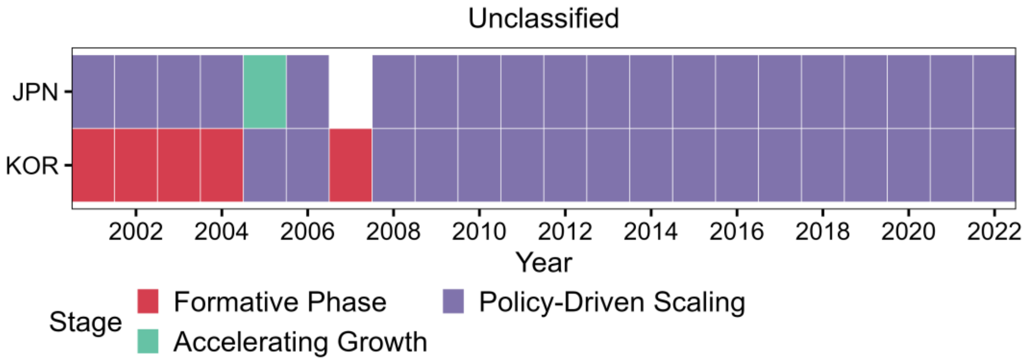

Fig. S27. Country-level onshore wind deployment stage trajectories by development path from 2000 to 2022

(**Path A: Front-Runners**) Country-year deployment stage trajectories for Path A Front-Runners, with stages colour-coded as policy-driven scaling (purple), accelerating growth (green), mature penetration (blue), early adoption (orange), and cost parity (yellow), and countries labelled by ISO-3 codes. (**Path B/C: Late Movers**) Corresponding trajectories for Path B/C Late Movers, with take-off year occurring after 2005. (**Path D: Laggards**) Trajectories for Path D Laggards under the same colour coding. (**Unclassified**) Trajectory for the unclassified country (JPN, ETH, MNG, LBN) restricted to the formative phase. White cells denote country-year observations excluded from the dataset. Deployment stages were described in the Methods.

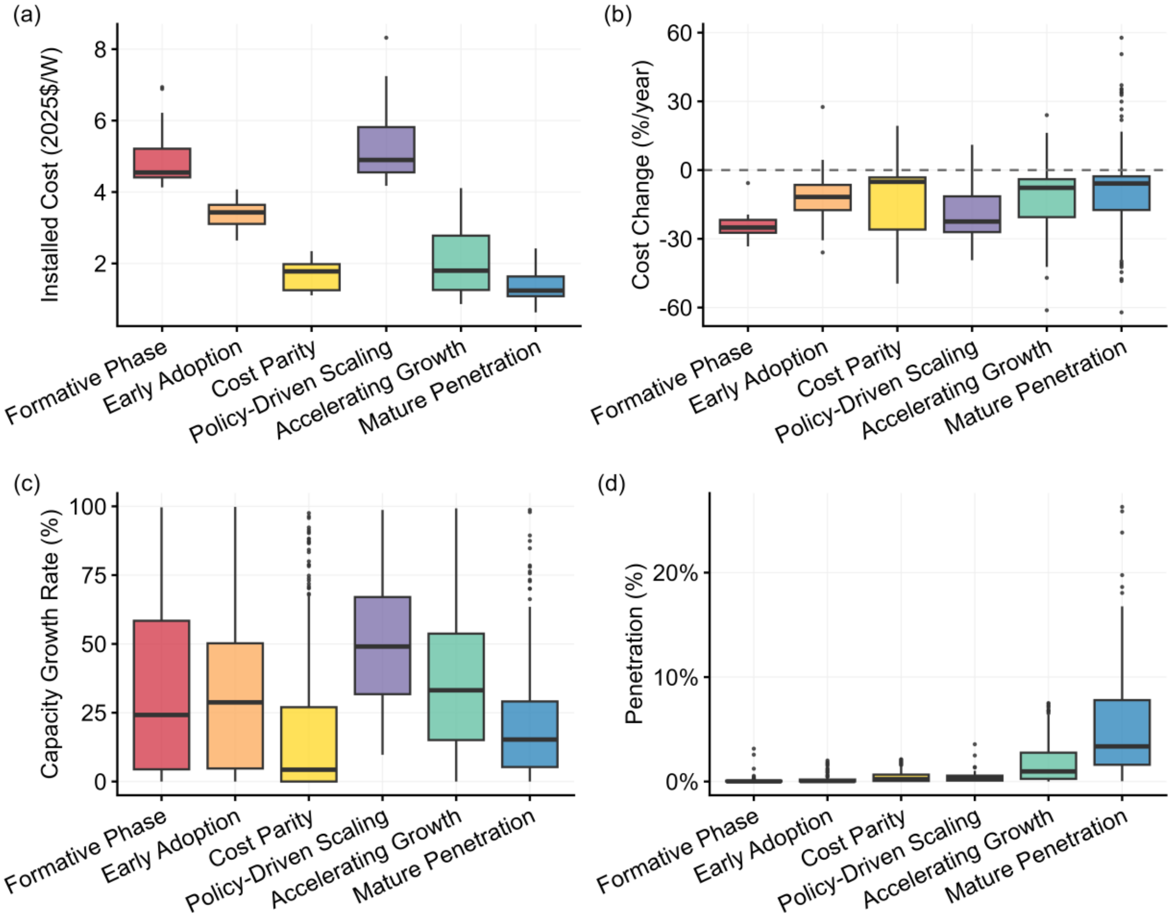

Fig. S28. Stage-wise distributions of installed cost, penetration, capacity growth rate, and annual cost change for solar PV

(**a**) Distributions of country-year installed cost (2025$/W) across the six deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration). (**b**) Distributions of annual installed cost change rate (% yr^{-1}) across the same stages, with the horizontal dashed line marking zero cost change. (**c**) Distributions of annual cumulative capacity growth rate (%) across the same stages. (**d**) Distributions of solar PV generation share of national electricity consumption (%) across the same stages. Boxes span the interquartile range (IQR) with the central line marking the median, whiskers extend to 1.5 × IQR, and points beyond denote outliers. Deployment stages were described in the Methods.

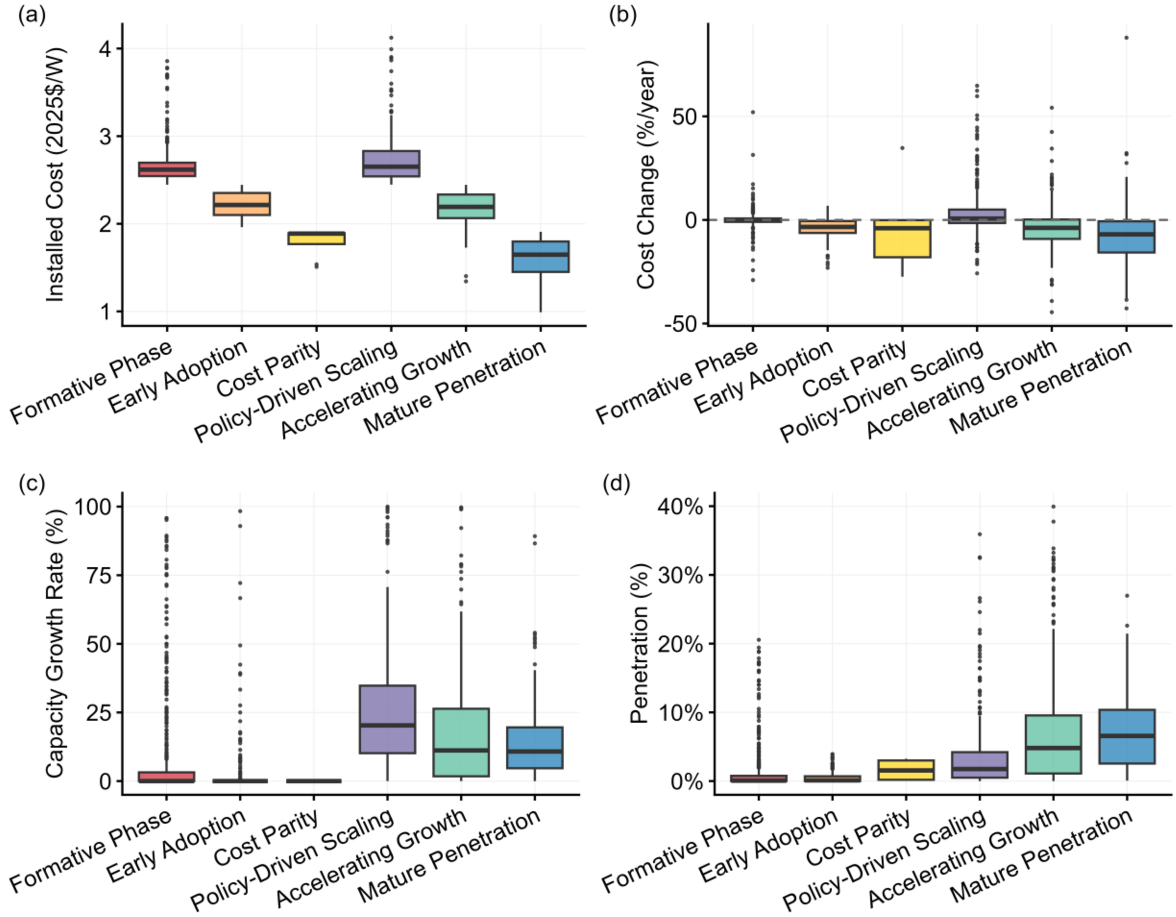

Fig. S29. Stage-wise distributions of installed cost, penetration, capacity growth rate, and annual cost change for onshore wind

(**a**) Distributions of country-year installed cost (2025$/W) across the six deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration). (**b**) Distributions of annual installed cost change rate (% yr^{-1}) across the same stages. (**c**) Distributions of annual cumulative capacity growth rate (%) across the same stages. (**d**) Distributions of onshore wind generation share of national electricity consumption (%) across the same stages. Boxes span the interquartile range (IQR) with the central line marking the median, whiskers extend to 1.5 × IQR, and points beyond denote outliers. Deployment stages were assigned from country-year cumulative capacity thresholds and capacity growth rates following the typology described in the Methods.

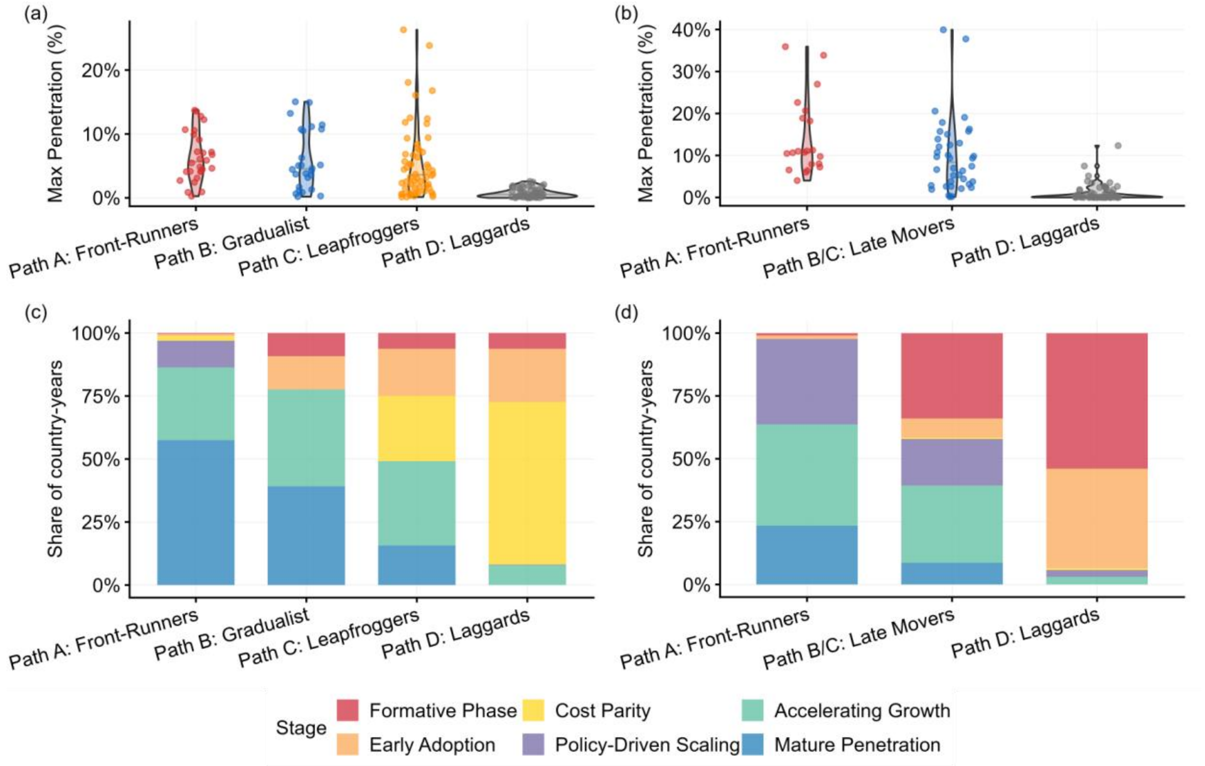

Fig. S30. Development-path stratified maximum penetration and deployment stage composition for solar PV and onshore wind

Maximum country-level penetration declined from Front-Runners to Laggards for both solar PV and onshore wind, and was mirrored by a systematic shift in deployment stage composition from mature penetration dominance in Front-Runners to cost parity and early adoption dominance in Laggards, with Leapfroggers and Late Movers occupying distinct intermediate compositions. Solar PV Leapfroggers achieved a maximum penetration distribution comparable to Front-Runners and Gradualists despite their later take-off, yet their deployment stage composition remained concentrated in cost parity, early adoption and accelerating growth rather than mature penetration, revealing a decoupling between peak penetration attainment and stage progression. (**a**) Country-level maximum solar PV penetration (% of national electricity generation) across the four development paths (Path A Front-Runners red, Path B Gradualists blue, Path C Leapfroggers orange, Path D Laggards grey), displayed as violin plots with overlaid individual country points. (**b**) Corresponding country-level maximum onshore wind penetration across the three development paths (Path A Front-Runners, Path B/C Late Movers, Path D Laggards). (**c**) Stacked composition of the six deployment stages (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration) as a share of country-year observations within each solar PV development path. (**d**) Corresponding stage composition within each onshore wind development path. Violin widths represent the kernel density of the penetration distribution within each path. Development paths and deployment stages were described in the Methods.

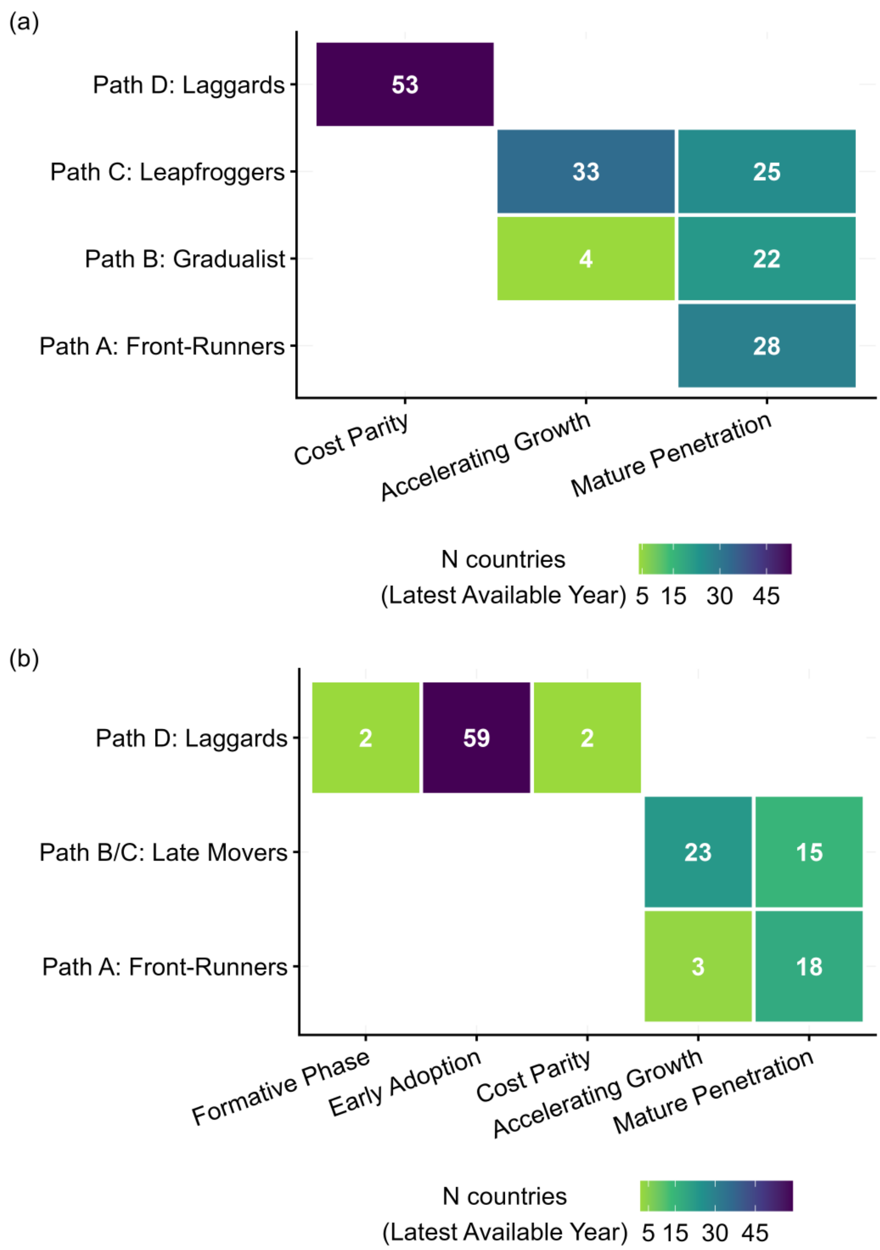

Fig. S31. Latest-year deployment stage distribution across development paths for solar PV and onshore wind

(**a**) Heatmap of the number of solar PV countries in each deployment stage during the latest available year, stratified by the four development paths (Path A Front-Runners, Path B Gradualists, Path C Leapfroggers, Path D Laggards), with cell colour indicating country count on a viridis scale and numerical labels reporting the exact count. (**b**) Corresponding heatmap for onshore wind, stratified by the three development paths (Path A Front-Runners, Path B/C Late Movers, Path D Laggards). Empty cells denote stage-path combinations with zero countries in the latest available year. Development paths were described in the Methods.

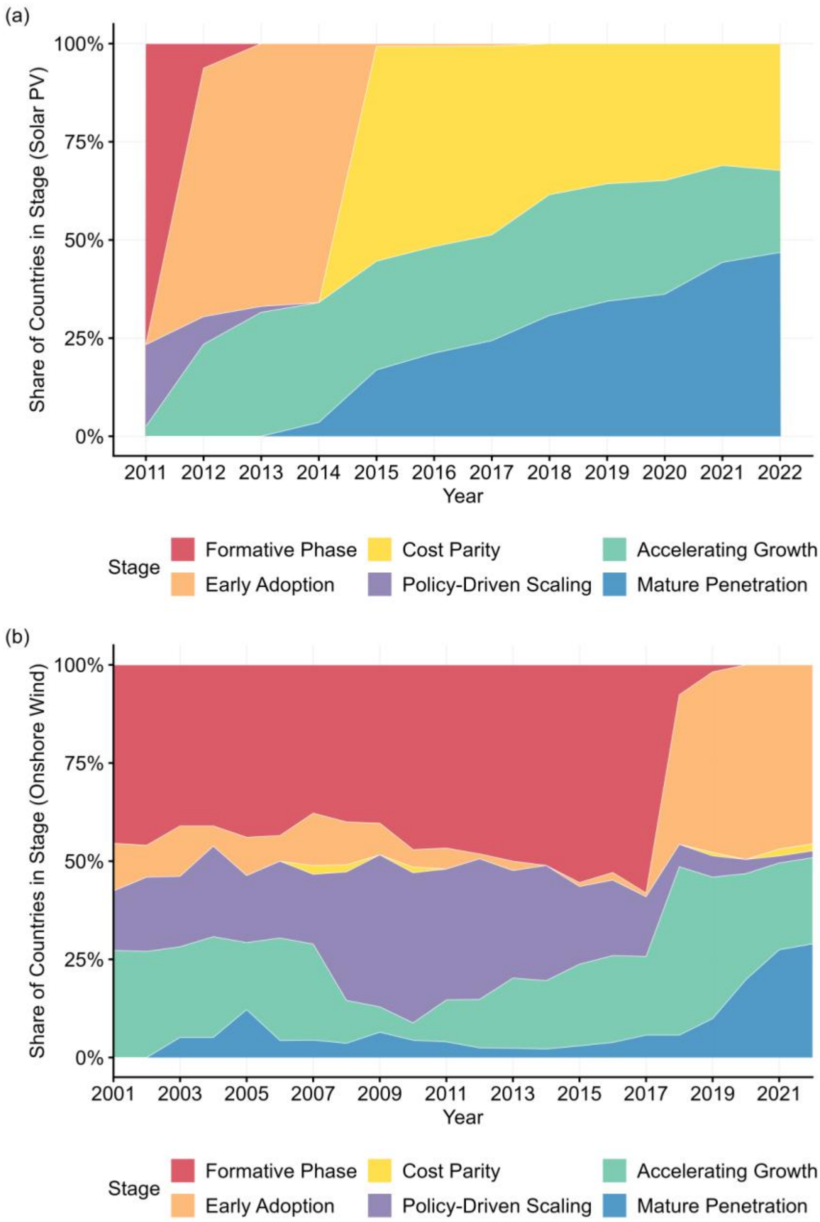

Fig. S32. Temporal evolution of deployment stage shares across countries for solar PV and onshore wind

Solar PV exhibited a rapid global stage transition, with cost parity dominance emerging by 2014 and mature penetration climbing from below 5% of countries in 2013 to above 45% by 2022, whereas onshore wind displayed a stagnant early adoption plateau spanning 2001 to 2017 before cost parity expanded after 2018, indicating a sharply divergent pace of stage progression between the two technologies. (**a**) Annual share of countries in each deployment stage (formative phase, early adoption, cost parity, policy-driven scaling, accelerating growth, mature penetration) for solar PV from 2011 to 2022, displayed as a stacked area plot summing to 100%. (**b**) Corresponding annual share of countries in each deployment stage for onshore wind from 2001 to 2022. Deployment stages were described in the Methods.

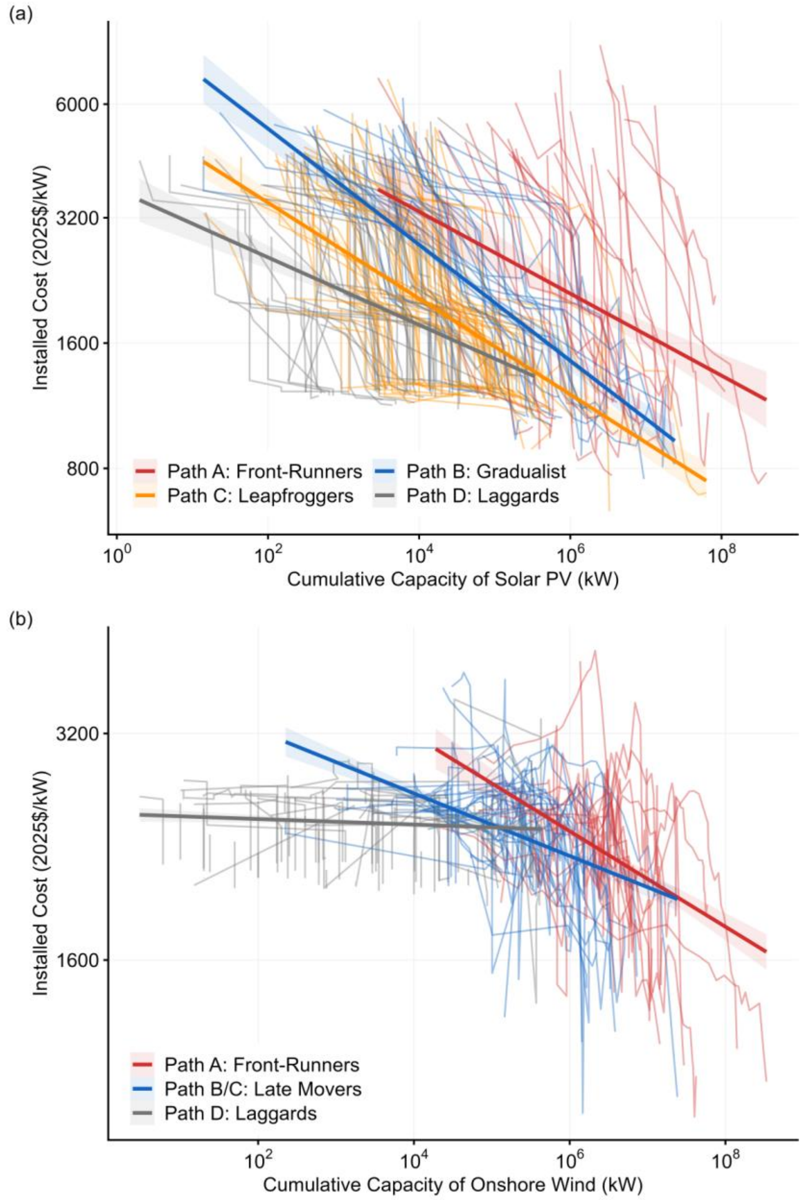

Fig. S33. Installation cost versus cumulative capacity by development path for solar PV and onshore wind

Solar PV installation cost declined consistently with cumulative capacity across all four development paths, whereas onshore wind exhibited a markedly weaker cost-capacity association, with Laggards displaying a nearly flat fit near 2200 $ kW^{-1}, and Front-Runners producing a clear negative slope at the high-capacity end of the observed range. (**a**) Country-level installation cost (2025$ kW^{-1}, log scale) plotted against cumulative installed capacity (kW, log scale) for solar PV, with thin lines tracing individual country trajectories and thick lines showing the ordinary least squares linear fit of log-transformed cost on log-transformed cumulative capacity within each development path (Path A Front-Runners red, Path B Gradualists blue, Path C Leapfroggers orange, Path D Laggards grey), where shaded bands denote the 95% confidence interval of the fit. (**b**) Corresponding country-level cost-capacity relationship for onshore wind, stratified by the three development paths (Path A Front-Runners, Path B/C Late Movers, Path D Laggards) under the same plotting convention. The fitted lines represent cross-country log-linear associations within each development path. Development paths were described in the Methods.

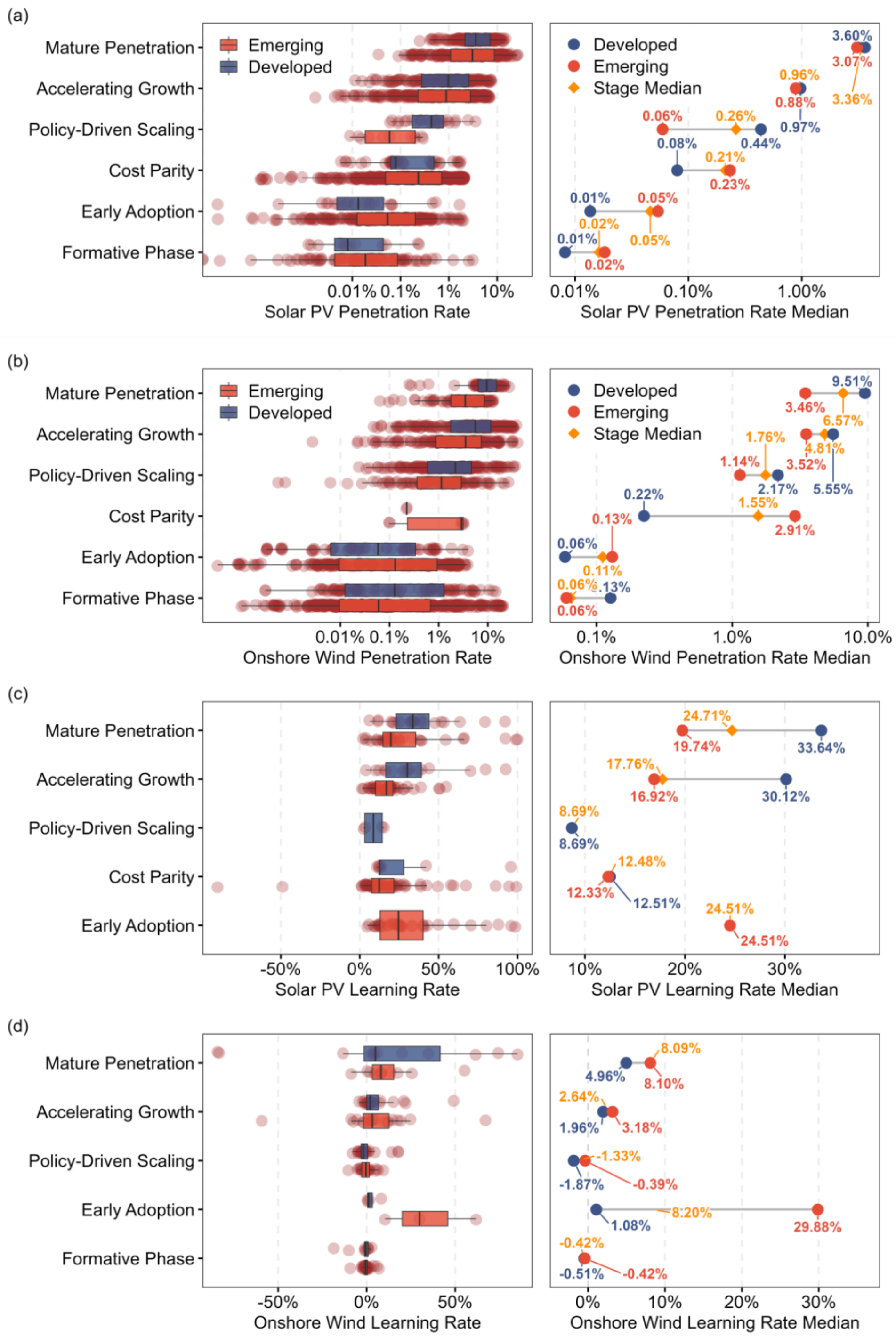

Fig. S34. Stage-wise country-level penetration and learning rates stratified by economy type for solar PV and onshore wind

(**a**) Country-level solar PV penetration rate (% of national electricity generation, log scale) distributions by deployment stage and economy type, with the left panel showing box plots and jittered country-year observations and the right panel reporting the median within each stage-economy combination alongside the overall stage median (orange diamonds). (**b**) Corresponding distributions and medians for onshore wind penetration rate. (**c**) Country-level solar PV learning rate (% cost reduction per doubling of cumulative capacity) distributions by deployment stage and economy type. (**d**) Corresponding distributions and medians for onshore wind learning rate. Boxes span the interquartile range (IQR) with central lines marking the median and whiskers extending to 1.5 × IQR. Deployment stages and learning rates were described in the Methods. Country classification follows the IMF developed versus emerging market taxonomy.

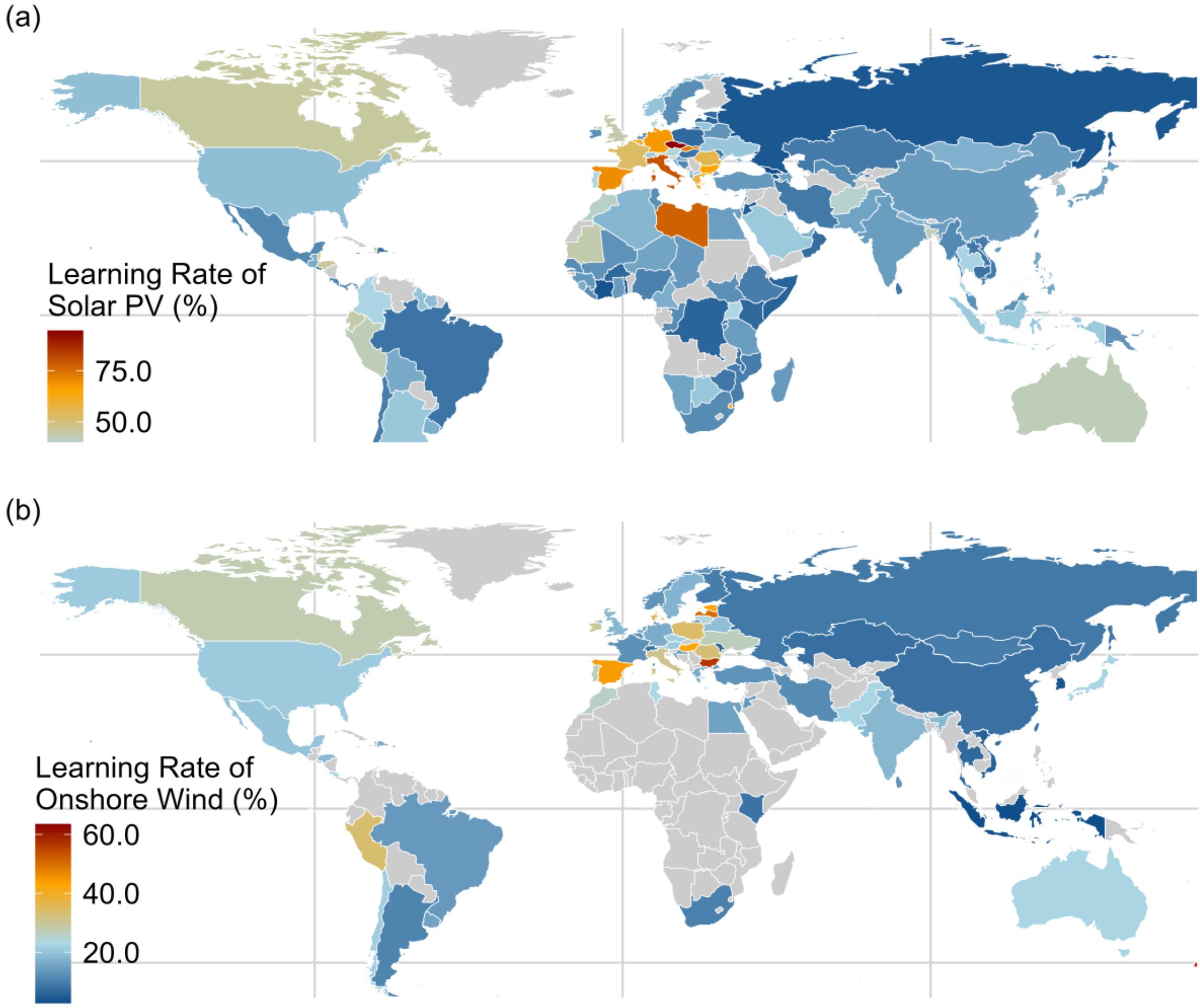

Fig. S35. Country-level learning rate distributions for solar PV and onshore wind

Solar PV learning rates exceeded 50% across multiple European countries and Libya, while onshore wind learning rates remained predominantly below 30% globally, with Peru, Spain, and several Central European countries forming the narrow 40-60% upper tail, indicating substantially stronger and more geographically widespread cost-reduction performance for solar PV than for onshore wind. (**a**) Country-level choropleth of solar PV learning rate (% cost reduction per doubling of cumulative capacity), with grey denoting countries excluded from the learning-rate estimation domain. (**b**) Corresponding country-level choropleth of onshore wind learning rate, with a colour scale capped at 60% reflecting the narrower empirical range for onshore wind. Learning rates were described in the Methods.

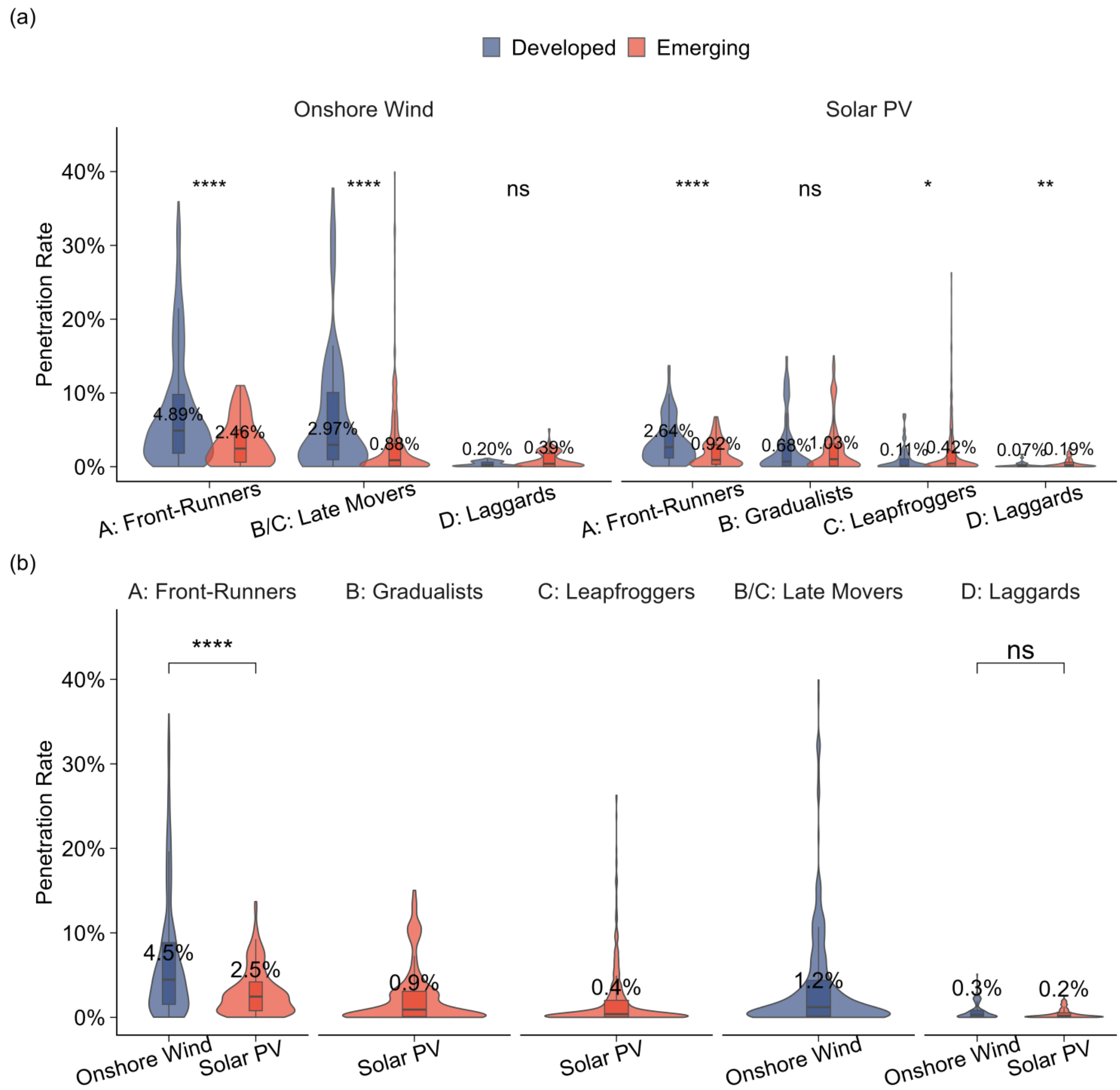

Fig. S36. Penetration rate distributions stratified by development path, economy type, and technology

(**a**) Country-level penetration rate distributions across development paths for onshore wind (left group) and solar PV (right group), separated into developed (blue) and emerging (red) economies, with violin widths representing the kernel density, embedded box plots spanning the interquartile range, median values labelled, and significance annotations from two-sided Wilcoxon rank-sum tests (ns not significant, *p < 0.05, **p < 0.01, ****p < 0.0001). (**b**) Within-path cross-technology comparison of penetration rate distributions, with each panel showing the technologies present in that path and significance annotations following the same convention. Development paths were classified from the joint distribution of take-off year and diffusion speed, and country classification follows the IMF developed versus emerging market taxonomy. Paths with a single technology (Gradualists, Leapfroggers for solar PV only; Late Movers for onshore wind only) are shown without cross-technology significance annotations.

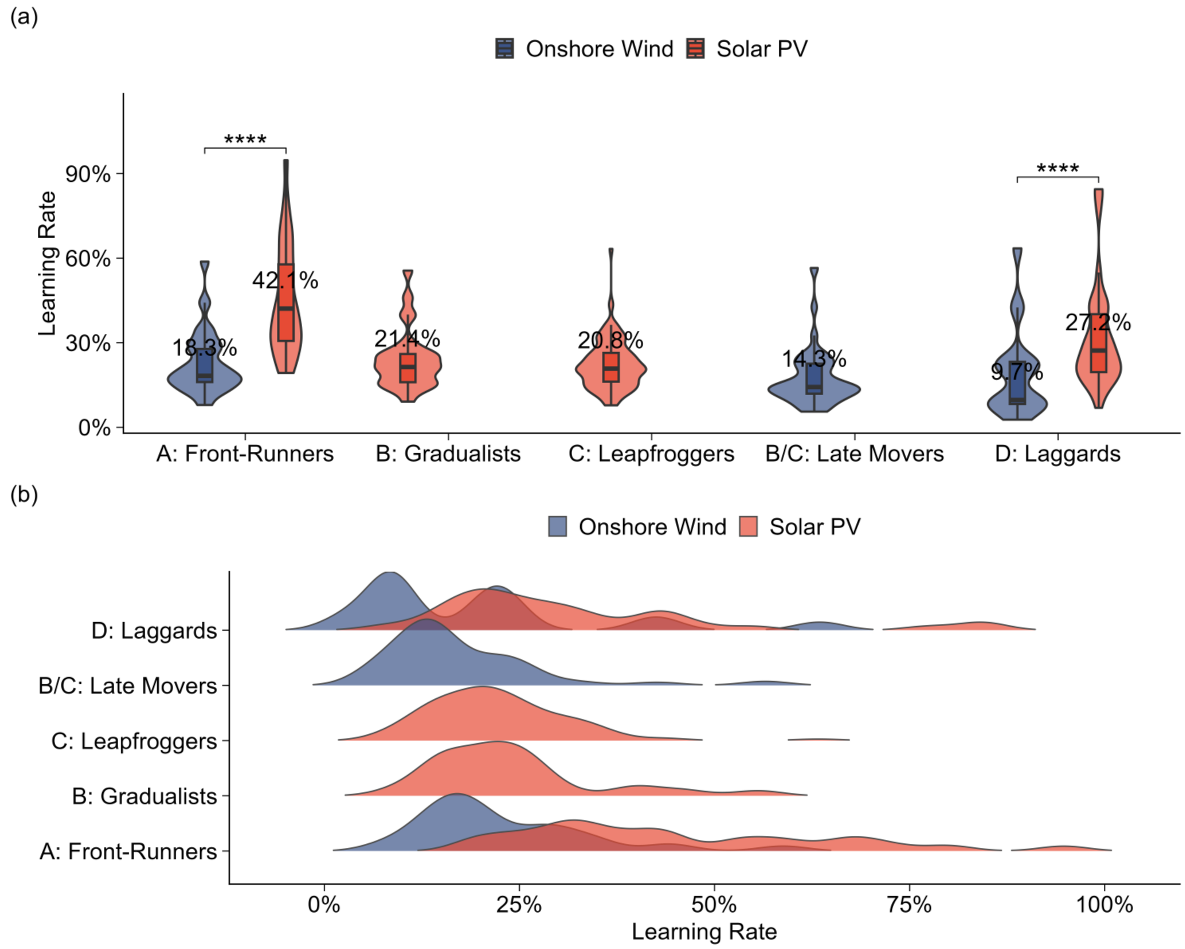

Fig. S37. Learning rate distributions by development path for solar PV and onshore wind

(**a**) Country-level learning rate distributions by development path (Path A Front-Runners, Path B Gradualists, Path C Leapfroggers, Path B/C Late Movers, Path D Laggards) for onshore wind (blue) and solar PV (red), displayed as violin plots with embedded box plots, median values labelled, and significance annotations from two-sided Wilcoxon rank-sum tests (**** $p < 0.0001$). (**b**) Density ridgeline representation of the same learning rate distributions for each development path, with onshore wind (blue) and solar PV (red) densities overlaid for direct shape comparison. Learning rates were and development paths were described in the Methods.

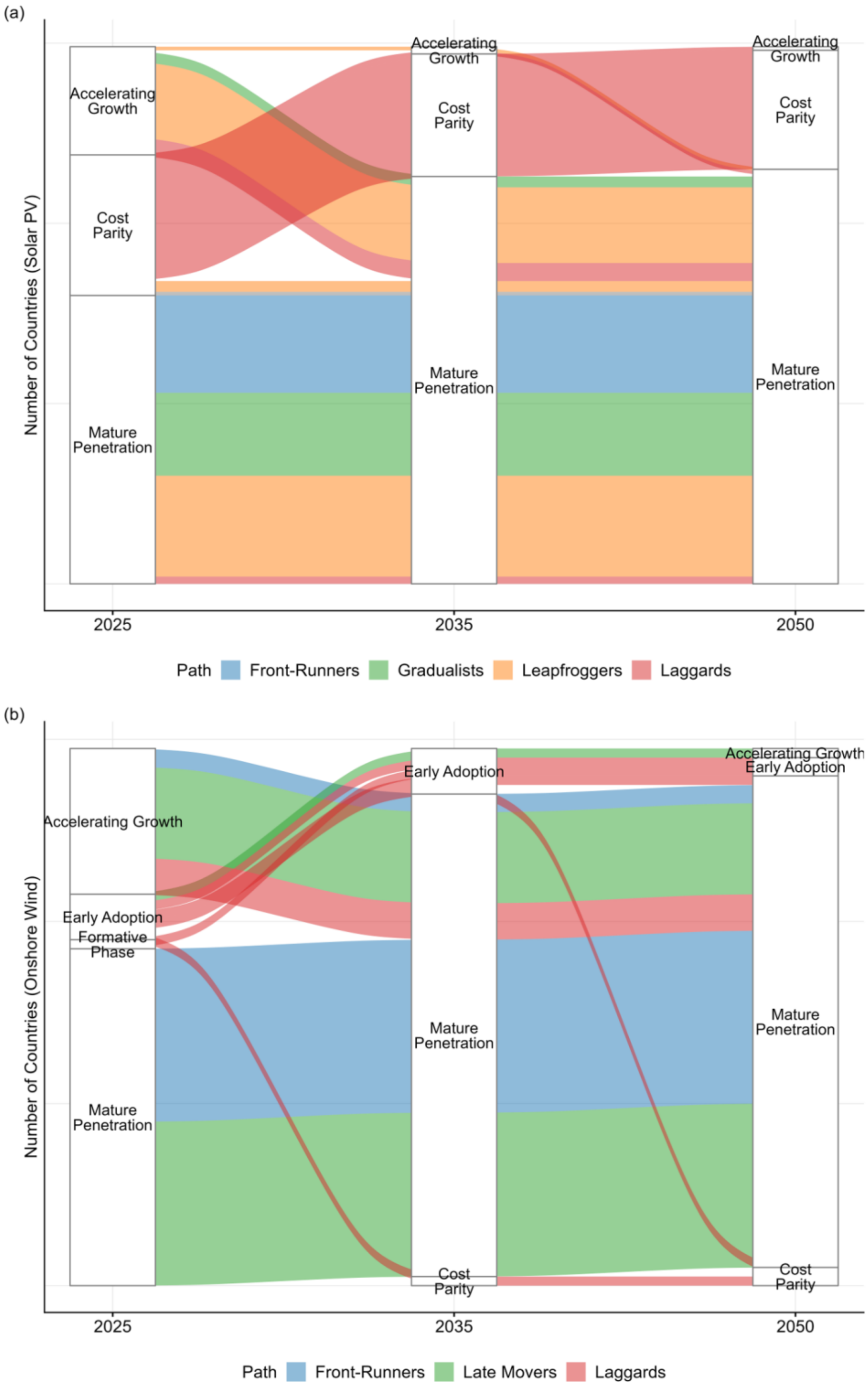

Fig. S38. Projected country-level deployment stage transitions from 2025 to 2050 by development path for solar PV and onshore wind

(**a**) Alluvial diagram of projected country-level deployment stage transitions for solar PV across three snapshot years (2025, 2035, 2050), with ribbons coloured by development path (Front-Runners blue, Gradualists green, Leapfroggers orange, Laggards red) and ribbon width proportional to the number of countries following each stage-to-stage trajectory. (**b**) Corresponding alluvial diagram for onshore wind. Deployment stages and development paths were described in the Methods.

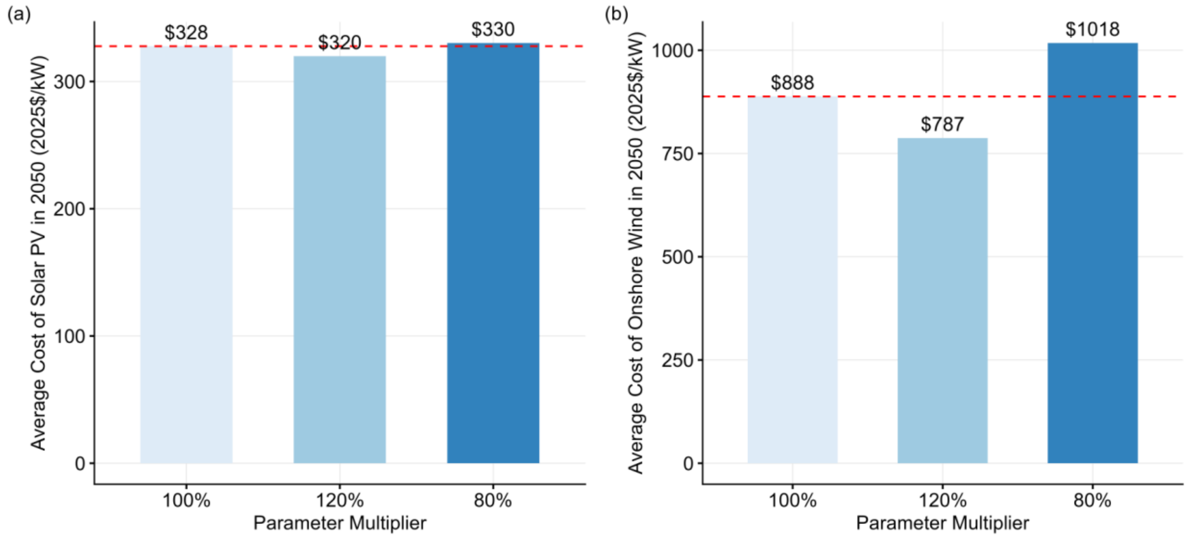

Fig. S39. Parameter sensitivity of projected 2050 installation cost for solar PV and onshore wind

(**a**) Average 2050 solar PV installation cost (2025\$ kW^{-1}) under three parameter multiplier scenarios (baseline 100%, upward perturbation 120%, downward perturbation 80%), with the red dashed line marking the baseline reference value and numerical labels reporting the exact average cost for each scenario. (**b**) Corresponding average 2050 onshore wind installation cost. The parameter multiplier uniformly SCALE the key model parameters identified in the sensitivity analysis framework described in the Methods, and the reported cost represents the cross-country average of projected 2050 values.

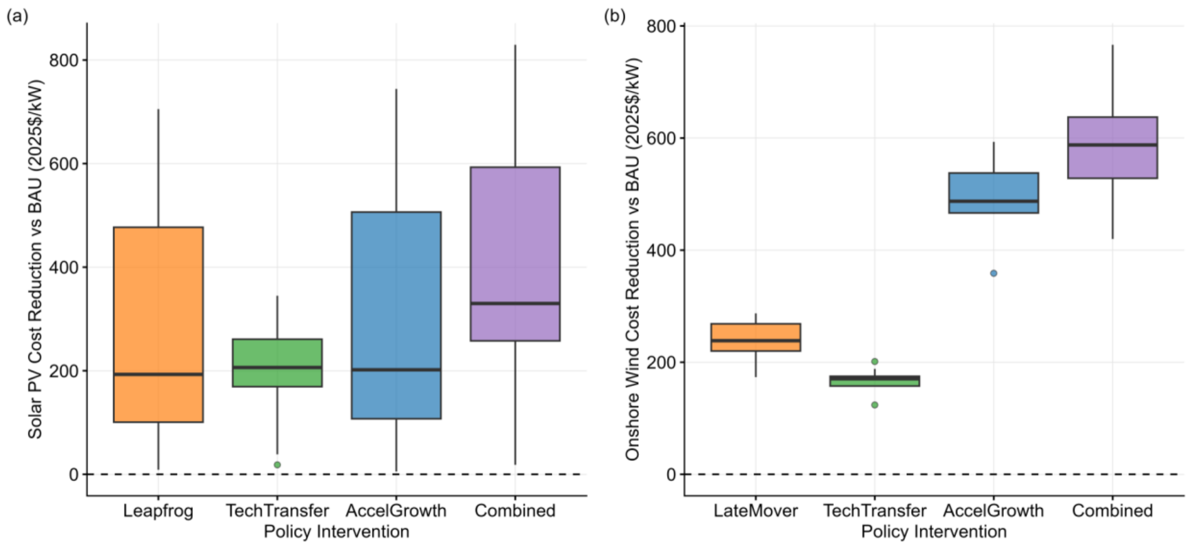

Fig. S40. Policy-intervention induced cost reduction relative to business-as-usual projection for solar PV and onshore wind

(**a**) Distributions of country-level solar PV installation cost reduction (2025\$ kW^{-1}) relative to the business-as-usual projection under four policy interventions (Leapfrog acceleration, technology transfer, accelerated growth, combined package), with the horizontal dashed line marking zero reduction. (**b**) Corresponding distributions of country-level onshore wind installation cost reduction under four policy interventions (Late Mover acceleration, technology transfer, accelerated growth, combined package) with the same zero-reduction reference line. Boxes span the interquartile range (IQR) with central lines marking the median and whiskers extending to 1.5 × IQR. Policy interventions were simulated by modifying the diffusion and learning parameters of the projection model following the intervention framework described in the Methods.

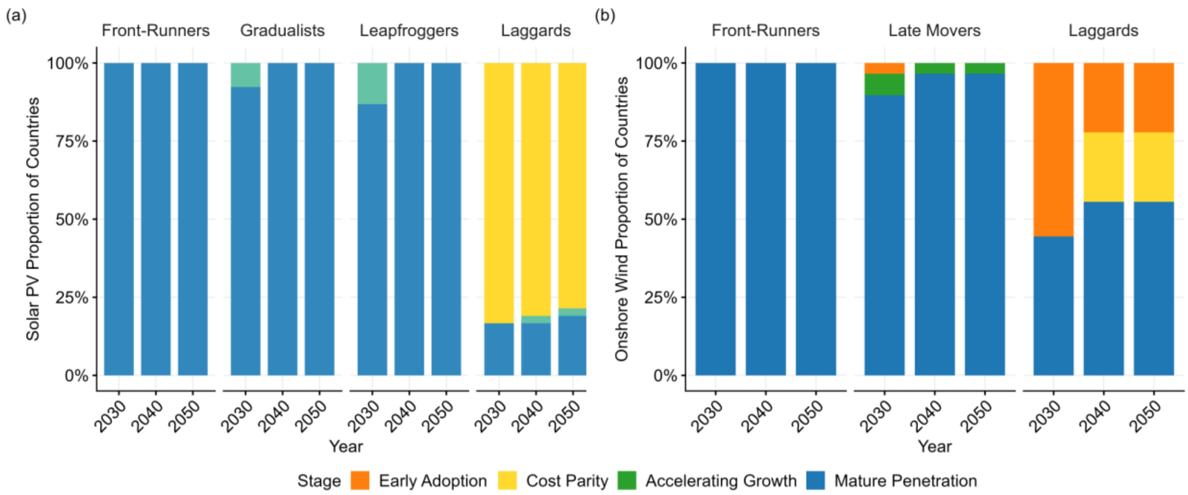

Fig. S41. Projected deployment stage distribution by development path across 2030, 2040, and 2050 for solar PV and onshore wind

(**a**) Stacked composition of projected deployment stages as a share of countries within each solar PV development path (Front-Runners, Gradualists, Leapfroggers, Laggards) for the three snapshot years 2030, 2040, and 2050, with stage colour coding following mature penetration (blue), cost parity (yellow), accelerating growth (green), and early adoption (orange). (**b**) Corresponding stacked composition for onshore wind, stratified by the three development paths (Front-Runners, Late Movers, Laggards). Deployment stages and development paths were described in the Methods.

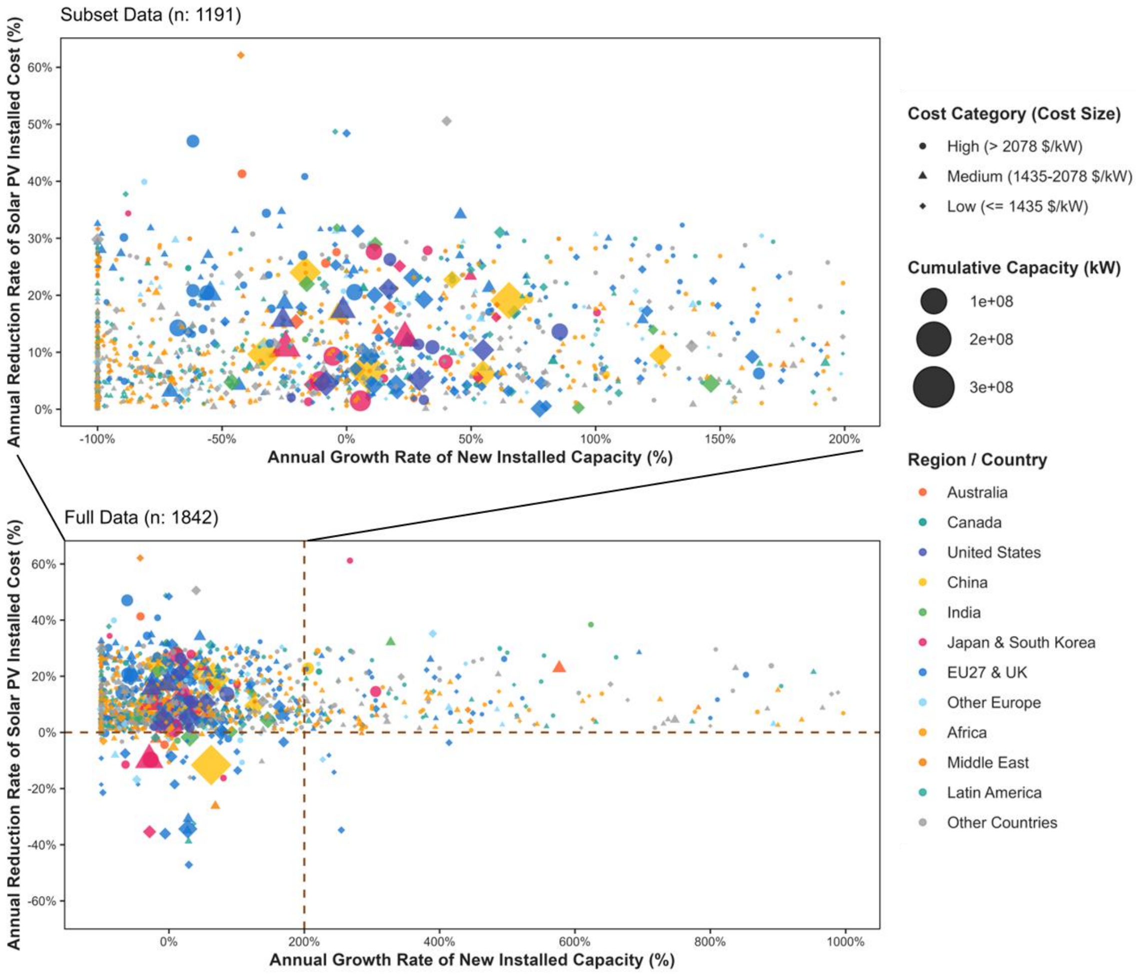

Fig. S42. Annual solar PV installation cost reduction rate versus new capacity growth rate across countries and regions

(**a**) Zoomed subset view (n=1191 country-year observations) restricted to capacity growth rates between -100% and 200%, with marker size proportional to cumulative installed capacity (kW), marker shape indicating cost category (circle high >2078 $ kW^{-1}, triangle medium 1435-2078 $ kW^{-1}, diamond low ≤1435 $ kW^{-1}), and colour denoting region or major single-country market (Australia, Canada, United States, China, India, Japan & South Korea, EU27 & UK, Other Europe, Africa, Middle East, Latin America, Other Countries). (**b**) Full-data view (n=1842) across the complete capacity growth rate range (-100% to 1000%), with the vertical dashed line marking the 200% threshold demarcating the subset shown in panel a, the horizontal dashed line marking zero cost reduction, and the same marker-size, shape, and colour conventions. Annual cost reduction rate was computed as the year-over-year percentage change in country-year installation cost, and annual new capacity growth rate was computed as the year-over-year percentage change in newly installed capacity.

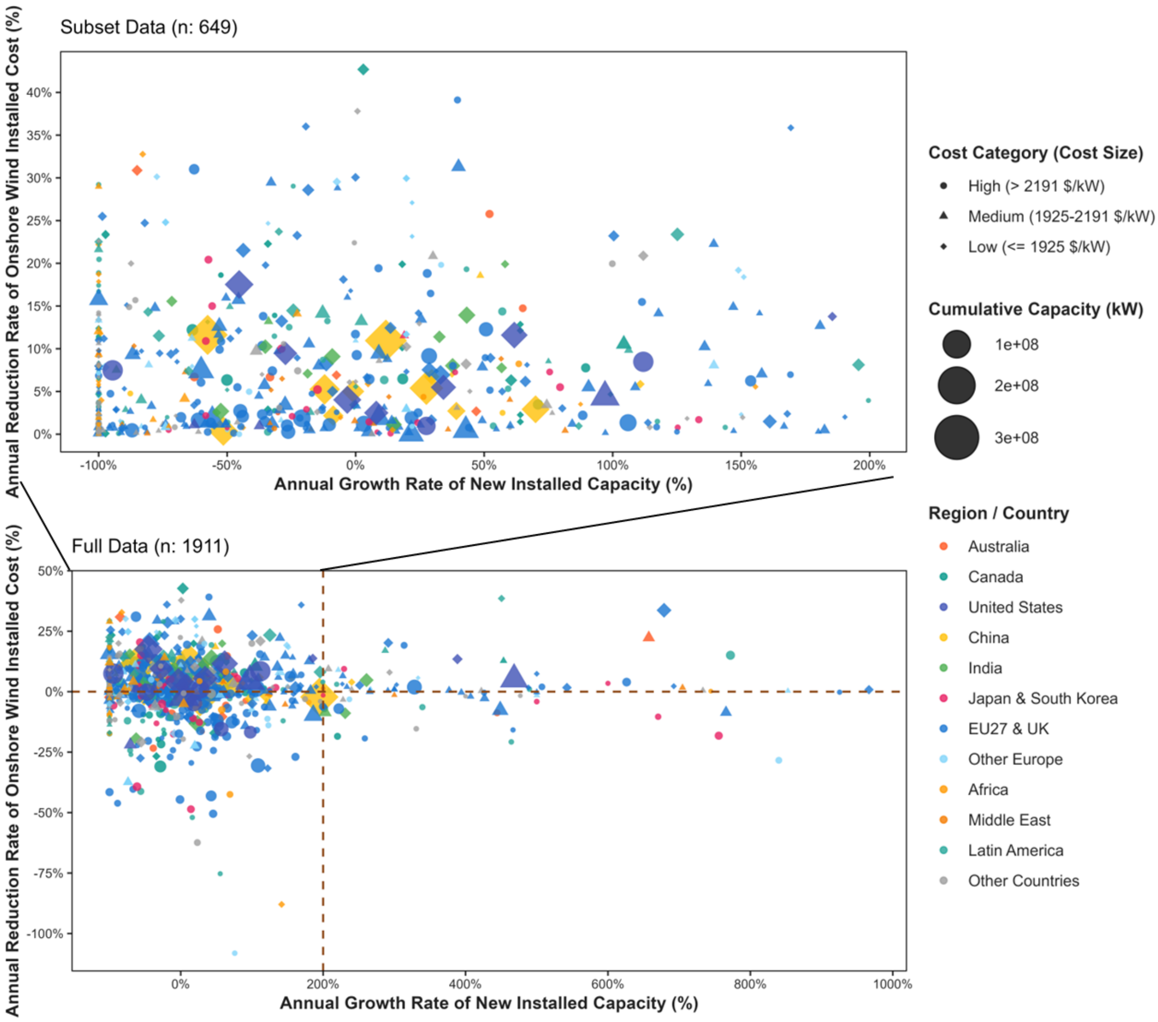

Fig. S43. Annual onshore wind installation cost reduction rate versus new capacity growth rate across countries and regions

(**a**) Zoomed subset view (n=649 country-year observations) restricted to capacity growth rates between -100% and 200%, with marker size proportional to cumulative installed capacity (kW), marker shape indicating cost category (circle high>2191 $ kW^{-1}, triangle medium 1925-2191 $ kW^{-1}, diamond low≤1925 $ kW^{-1}), and colour denoting region or major single-country market (Australia, Canada, United States, China, India, Japan & South Korea, EU27 & UK, Other Europe, Africa, Middle East, Latin America, Other Countries). (**b**) Full-data view (n=1911) across the complete capacity growth rate range (-100% to 1000%), with the vertical dashed line marking the 200% threshold demarcating the subset shown in panel a, the horizontal dashed line marking zero cost reduction, and the same marker conventions. Annual cost reduction rate was computed as the year-over-year percentage change in country-year installation cost, and annual new capacity growth rate was computed as the year-over-year percentage change in newly installed capacity.

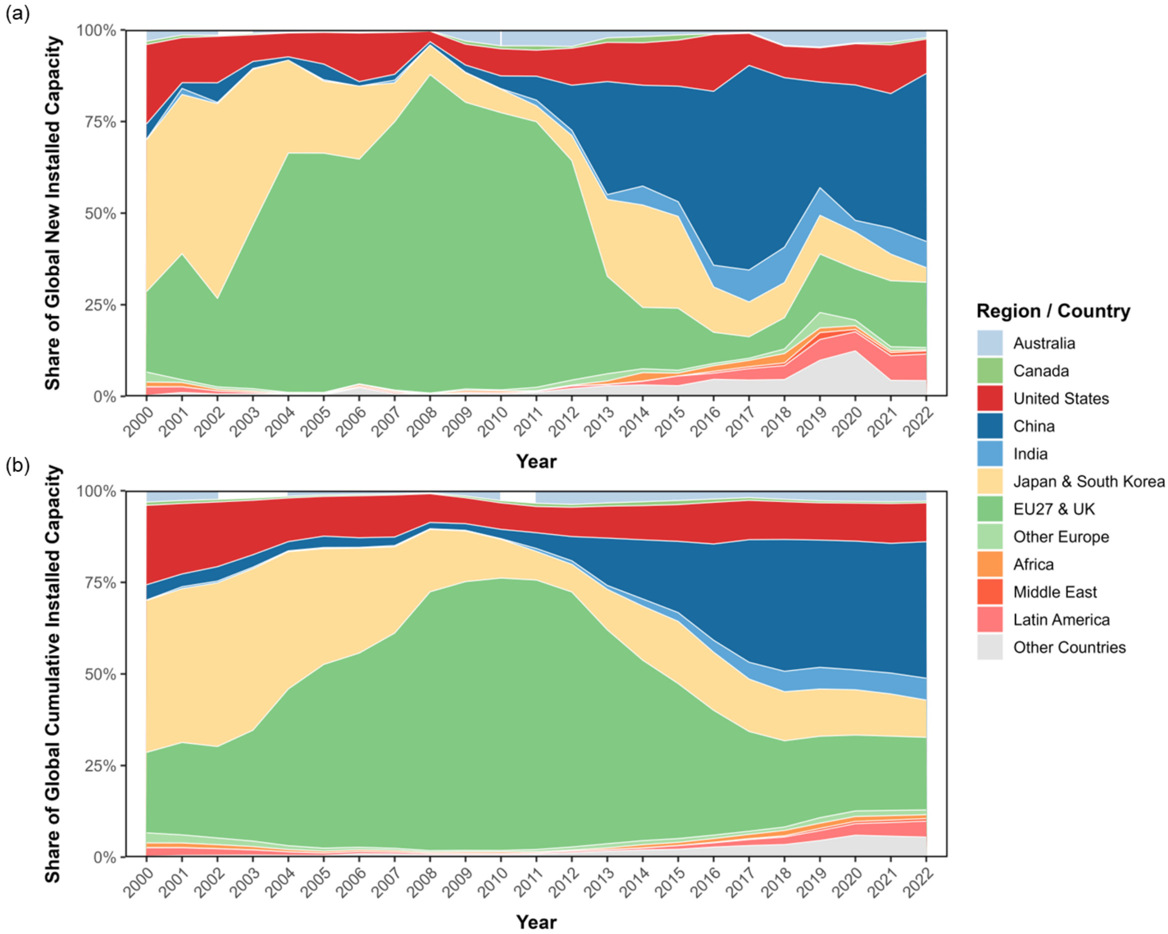

Fig. S44. Temporal evolution of regional shares of global solar PV new and cumulative installed capacity

(**a**) Stacked annual share of global new installed solar PV capacity (%) from 2000 to 2022, disaggregated by region or major single-country market (Australia, Canada, United States, China, India, Japan & South Korea, EU27 & UK, Other Europe, Africa, Middle East, Latin America, Other Countries). (**b**) Corresponding stacked annual share of global cumulative installed solar PV capacity (%) over the same period and regional disaggregation.

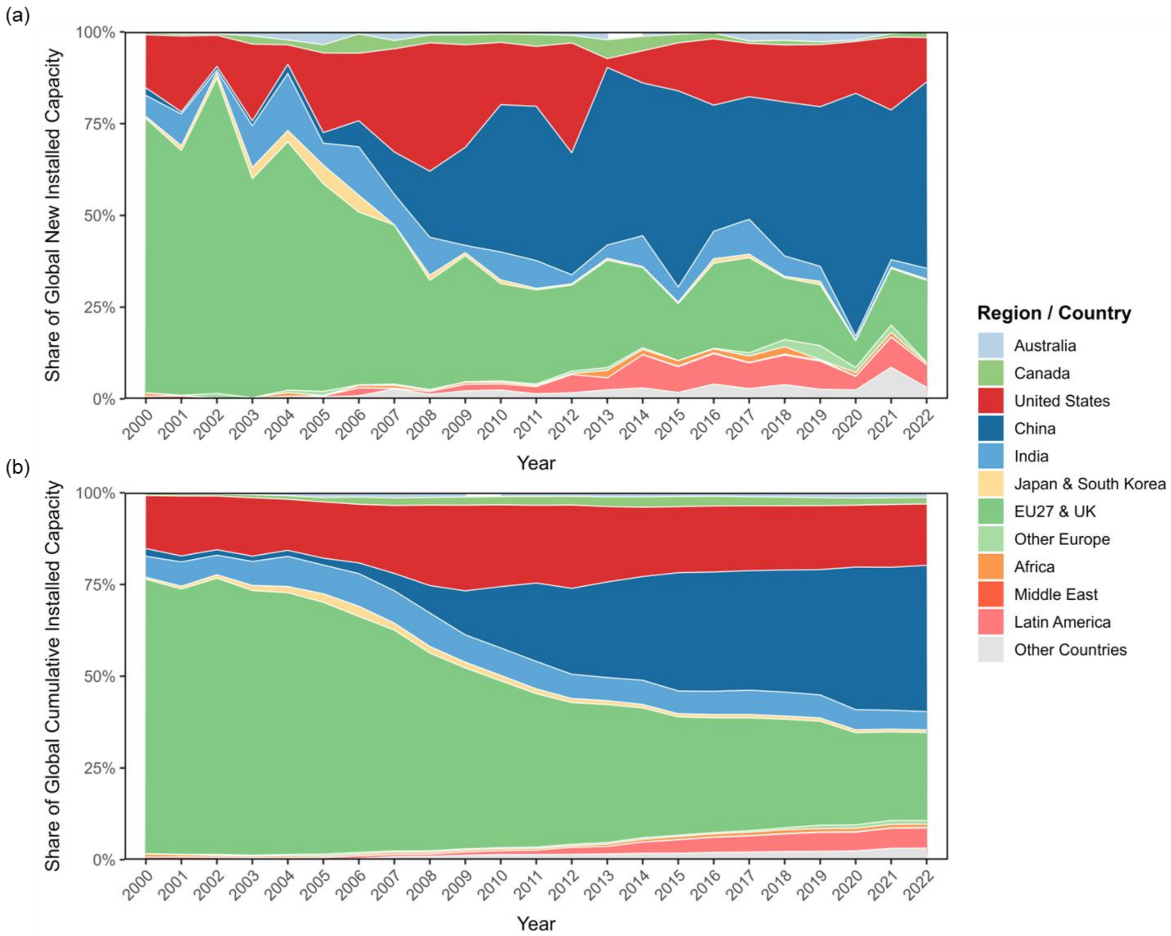

Fig. S45. Temporal evolution of regional shares of global onshore wind new and cumulative installed capacity

(**a**) Stacked annual share of global new installed onshore wind capacity (%) from 2000 to 2022, disaggregated by region or major single-country market (Australia, Canada, United States, China, India, Japan & South Korea, EU27 & UK, Other Europe, Africa, Middle East, Latin America, Other Countries). (**b**) Corresponding stacked annual share of global cumulative installed onshore wind capacity (%) over the same period and regional disaggregation.

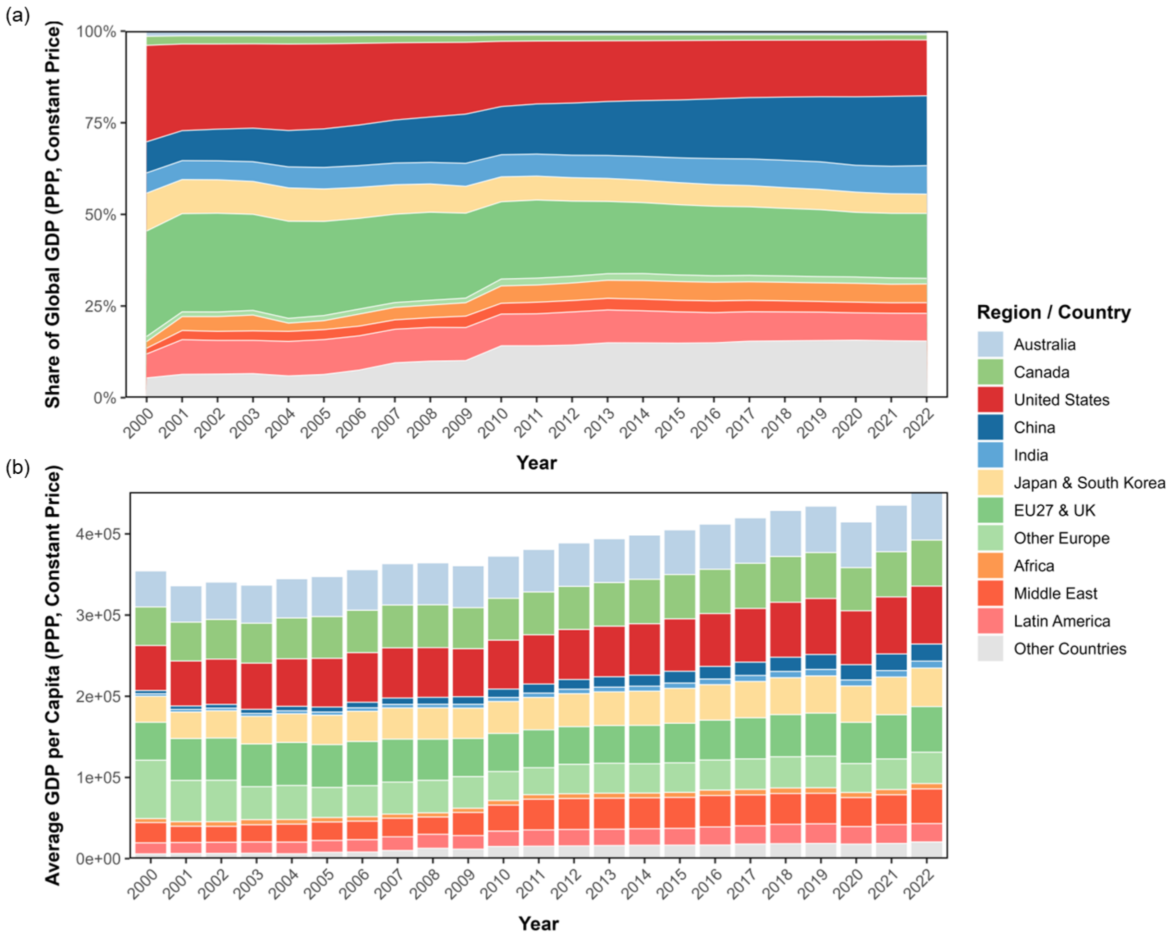

Fig. S46. Temporal evolution of regional shares of global GDP and regional per capita GDP
(**a**) Stacked annual share of global GDP (%, PPP, constant price) from 2000 to 2022, disaggregated by region or major single-country market (Australia, Canada, United States, China, India, Japan & South Korea, EU27 & UK, Other Europe, Africa, Middle East, Latin America, Other Countries). (**b**) Stacked annual per capita GDP (PPP, constant price) over the same period, summing regional contributions within each year.

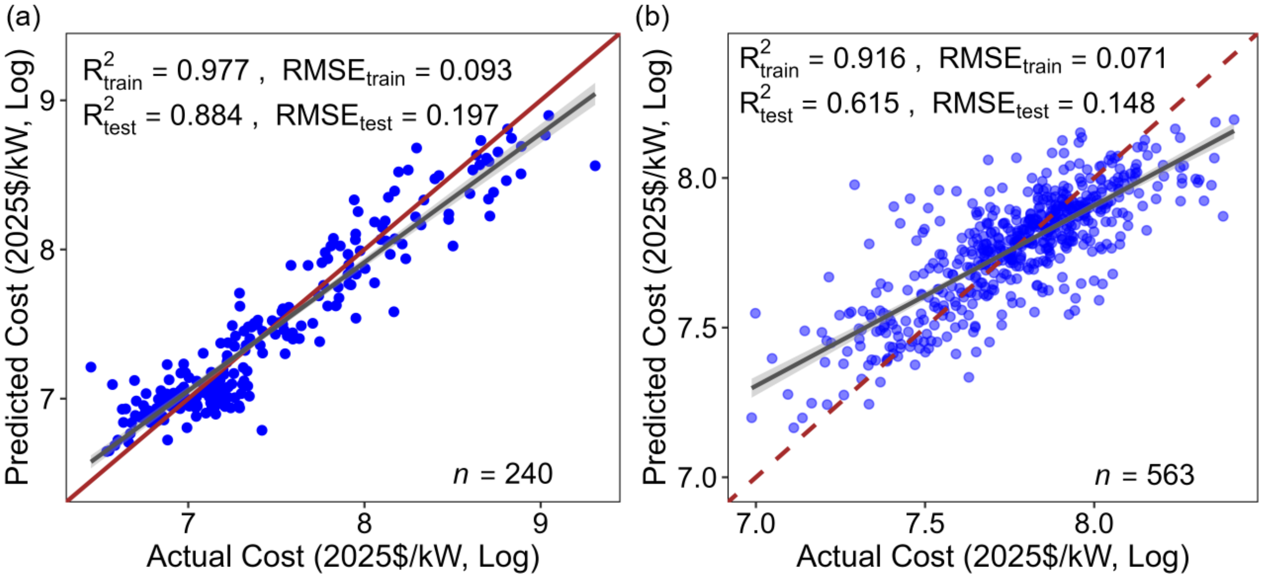

Fig. S47. Predicted and actual log-transformed installed costs for solar PV and onshore wind random forest models excluding cumulative capacity from the predictor set.

(**a**) Predicted against actual log-transformed solar PV installed cost with cumulative capacity as a predictor (2022 \$ kW⁻¹; n=240). (**b**) Predicted against actual log-transformed onshore wind installed cost with cumulative capacity as a predictor (n=563). Blue points denote individual country-year observations for testing dataset, the grey line shows the ordinary-least-squares fit with its 95% confidence band, and the red diagonal indicates the 1:1 reference. In-panel statistics report the coefficient of determination (R^2) and root-mean-square error (RMSE) on the training and held-out test partitions. RMSE is expressed in log-cost units.

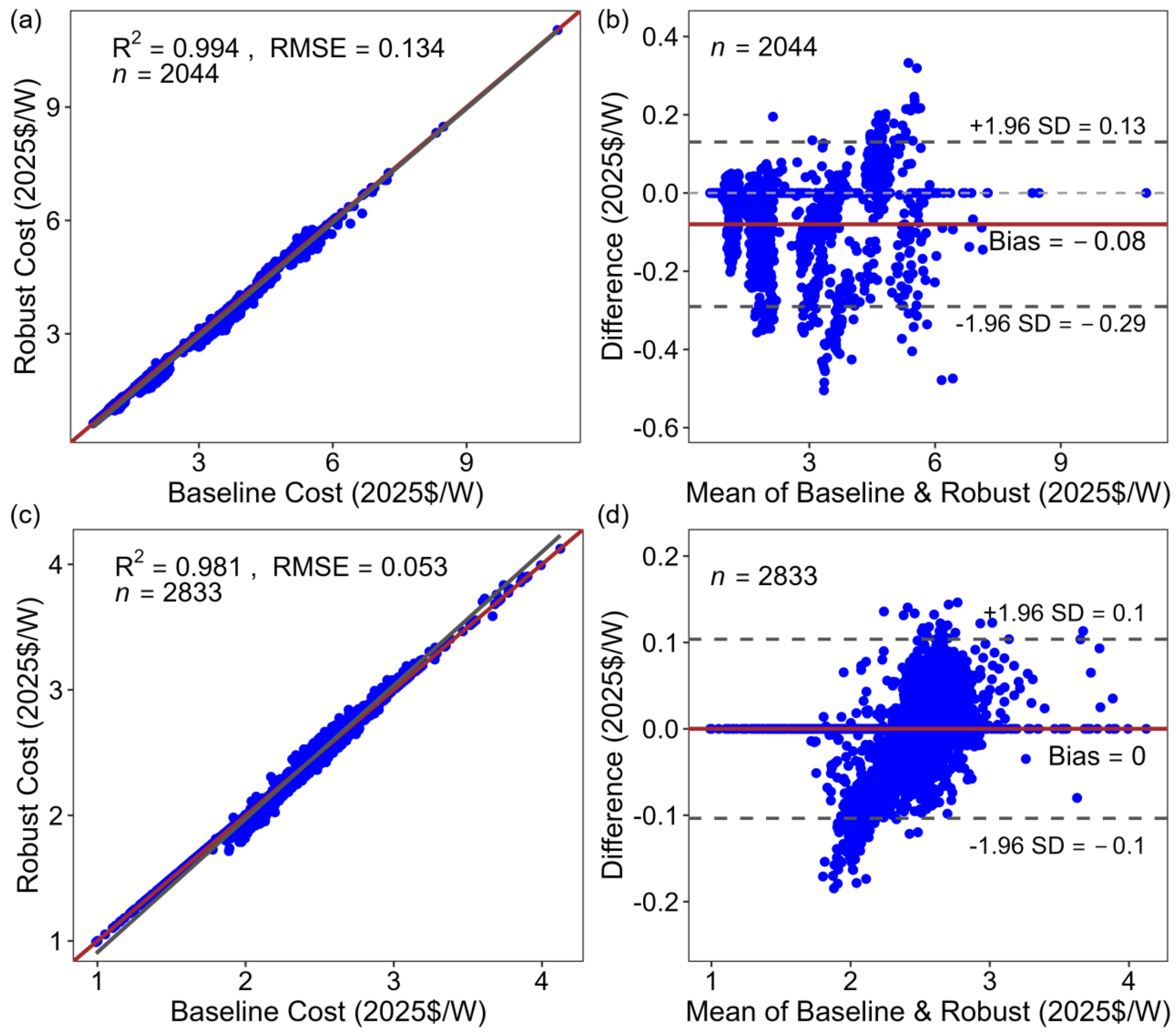

Fig. S48. Robustness comparison of random-forest cost estimates with and without installed capacity as a predictor.

(a) Solar PV cost estimates from the baseline random-forest model including installed capacity versus the robustness model excluding installed capacity. **(b)** Bland–Altman plot for solar PV, comparing the mean and difference between the baseline and robust estimates. **(c)** Onshore wind cost estimates from the baseline random-forest model including installed capacity versus the robustness model excluding installed capacity. **(d)** Bland–Altman plot for onshore wind, comparing the mean and difference between the baseline and robust estimates. In panels **b** and **d**, differences are calculated as robust estimate minus baseline estimate. The red line denotes the mean bias, and the dashed lines denote the ±1.96 standard deviation limits of agreement.

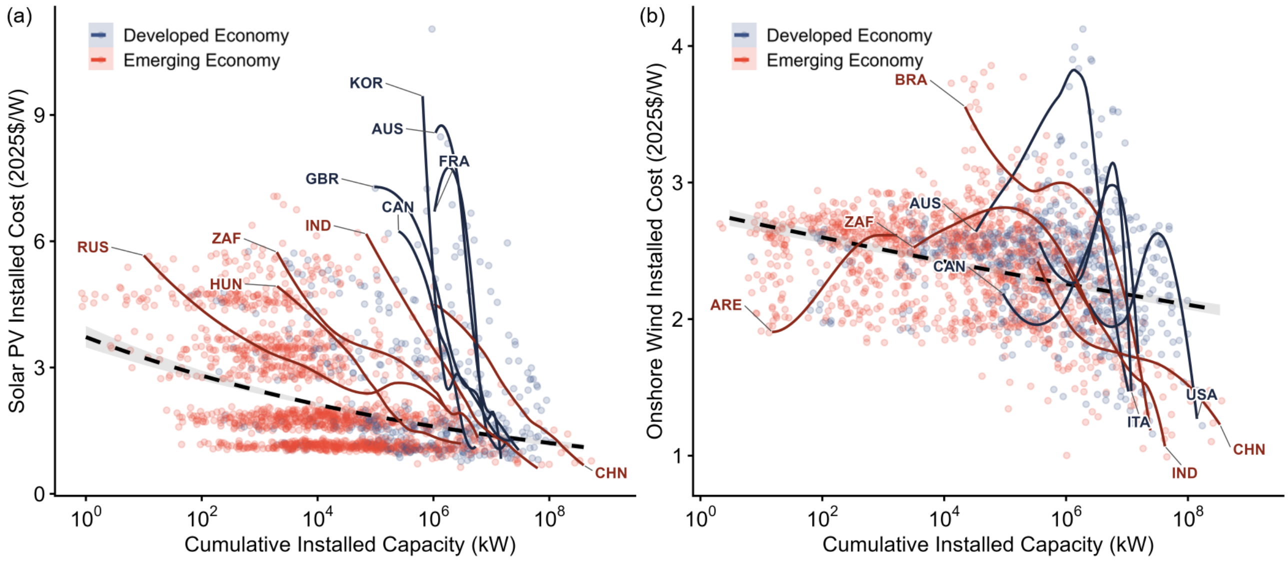

Fig. S49. Distribution of reconstructed onshore wind costs from the capacity-excluded random-forest model.

Installed cost (2025 US\$ W^{-1}) against cumulative installed capacity (kW, log scale) for solar PV over 2010–2022 (**a**) and onshore wind over 2000–2022 (**b**). Points denote country-year costs reconstructed by the capacity-excluded random-forest model; solid curves are country-specific LOESS fits for major markets (ISO-3) for developed (blue) and emerging (red) economies, classified by IMF criteria. Black dashed line denotes the global learning curve fitted across countries, with the shaded band showing the 95% confidence interval. All costs are harmonized to 2025 US dollars using a GDP deflator. LOESS, locally estimated scatterplot smoothing.

Supplementary Tables

Table S1. Threshold parameters and robustness evaluation across scenarios in the cascade-gated model

Threshold parameters and robustness metrics for the identification of take-off years under Relaxed, Base, and Strict scenarios. Penetration thresholds denote the required share of electricity generation, while growth thresholds denote the required new capacity ratio (for small systems) or Compound Annual Growth Rate (CAGR, for medium and large systems). Quantity fluctuation represents the absolute percentage change in the number of identified take-off countries relative to the Base scenario. Temporal stability denotes the share of jointly classified countries whose identified take-off year shifted by ≤2 years. No asterisk (*) indicates high consistency to threshold variations (i.e., quantity fluctuation ⩽ 25%, temporal stability ≥80%).

Technology	Scenario	Penetration (%) (Small / Med / Large)	Growth / Ratio (%) (Small Ratio / Med CAGR / Large CAGR)	Take-off Count	Quantity Fluctuation	Temporal Stability
Solar PV	Relaxed	0.5 / 1.5 / 2.5	3.0 / 15.0 / 15.0	54	22.7%	95.5%
	Base	1.0 / 2.0 / 3.5	5.0 / 20.0 / 20.0	44	-	-
	Strict	1.5 / 3.0 / 4.5	7.0 / 25.0 / 25.0	33	25.0%	97.0%
Onshore Wind	Relaxed	0.5 / 1.0 / 1.5	1.5 / 10.0 / 10.0	60	20.0%	94.0%
	Base	1.0 / 1.5 / 2.0	2.5 / 15.0 / 15.0	50	-	-
	Strict	1.5 / 2.0 / 3.0	4.0 / 20.0 / 20.0	41	18.0%	95.1%

Table S2. Historical calibration results of take-off years and supporting evidence for solar PV

The calibrated year is the earliest calendar year satisfying, simultaneously, an operational enabling policy instrument, at least one commissioned commercial-scale project (≥10 MW grid-connected), and annual capacity additions entering a sustained multi-year expansion (operationalized as ≥3 consecutive years of non-zero additions within the 5 years following the candidate year, or ≥2-fold capacity increase over that window). Countries exhibiting a single commissioned project followed by a plateau exceeding 4 years cannot satisfy criterion 3 and are classified as *no take-off* irrespective of cascade-gated detection.

Code	Country	FOBI Year	Cascade Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
BEL	Belgium	NA	2012	2009	Flanders Green Certificate scheme (2003, operational 2006); Walloon GC scheme (2008); residential Feed-In Tariff (FIT) extensions 2009.	Flemish rooftop capacity rose from 260 MWp (<10 kW systems, end-2009) to 1046 MWp (2012); Wallonia 41 MWp (2007-target) to 556 MWp (2012). No single anchoring project.	Cascade 2012 captures the plateau year after FIT cuts. Simultaneous fulfillment occurs in 2009 when GC revaluation and rooftop subsidy combined with sustained uptake.
BGR	Bulgaria	NA	2012	2011	Renewable Energy Act 2011; 20-year FIT and purchase obligation operational from May 2011.	Karadzhalovo 60.4 MW (2012); Pobeda 50.6 MW (2012). Capacity 6 MW (2009) → ~100 MW (2011) → >1,000 MW (mid-2012); only ~12 MW added 2013–2014.	Cascade 2012 captures mid-boom visibility. 2011 Act is the policy-commissioning-expansion convergence year.
BOL	Bolivia	NA	2013	2014	Economic and Social Development Plan 2016–2020 and 2025 Agenda framework (operational 2014).	Cobija 5.2 MW, off-grid (inaugurated 2014; operations 2015) → Yunchará 5 MW (Apr 2018) → Uyuni 60 MW (Sep 2018) → Oruro I 50 MW (Sep 2019). State-led sequential	Cascade 2013 predates commissioning; calibrated to 2014. Small market with state-led sequential commissioning.

Code	Country	FOBI Year	Cascade Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
						build-out; no IPP market.	
BRA	Brazil	NA	2012	2014	ANEEL Normative Resolution 482 (April 2012, net-metering) combined with 6th Reserve Energy Auction (October 2014, solar-exclusive).	Oct 2014 reserve auction: 31 projects, 889.7 MW (AC); Auction-backed pipeline: 0.9 GW (2014) → 2.0 GW (2015) → cumulative 2.5 GW (2018) → 55 GW (2025).	Cascade 2012 captures the regulatory onset. The 2014 auction is the operational trigger for utility-scale deployment; simultaneous fulfillment occurs in 2014.
CHL	Chile	NA	2014	2014	Law 20.571 Net-Billing Law (2012, technical norms 2014); non-conventional renewable energy quota (Law 20.257 of 2008).	Amanecer 100 MW and San Andrés 50 MW grid-connected Q1 2014; Salvador 70 MW (Nov 2014). Capacity ~7 MW (2013) → 848 MW (2015) → ~1.6 GW (2016).	Cascade 2014 retained. Market-driven (no subsidy); all three criteria met in 2014 via technical norms plus first utility-scale wave.
GRC	Greece	NA	2012	2010	Law 3851/2010 (RES acceleration law, operational June 2010) replacing Law 3468/2006; rooftop FIT of €0.55/kWh from June 2009.	First major market year 2010: ~150 MW installed and connected. Capacity 46 MW (2009) → 202 (2010) → 631 (2011) → 1536 (2012) → 2579 (2013).	Cascade 2012 captures peak-year visibility. 2010 is the first year of simultaneous fulfillment; FIT, commissioning, and acceleration all converge.
LKA	Sri Lanka	NA	2016	2016	Soorya Bala Sangramaya programme (Battle for Solar Energy), launched September 2016; Net-Accounting and Net-Plus schemes.	Laugfs 20 MW (Oct 2016) and Sagasolar 10 MW (Dec 2016), first utility-scale plants. Rooftop 126.9 MW / 11497 systems by Oct 2018.	Cascade 2016 retained. Policy launch, first net-accounting installations, and multi-year sustained growth all coincide in 2016.
NAM	Namibia	NA	2017	2015	Interim Renewable Energy Feed-In Tariff (REFIT),	Omburu 4.5 MW (InnoSun, 13 May 2015), first IPP plant; 14	Cascade 2017 captures the mid-REFIT visibility. 2015 is

Code	Country	FOBI Year	Cascade Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
					operational April 2015 (NamPower, Ministry of Mines and Energy, ECB).	REFIT IPPs × 5 MW (13 PV, 1 wind), 13 CODs 2016–2018. Capacity 5 MW (2015) → 97 MW (2018).	the first simultaneous year, with policy onset and Omburu commissioning anchoring the REFIT pipeline.
POL	Poland	NA	2014	2016	Renewable Energy Sources Act 2015 (adopted February 2015, auction system operational July 2016).	First auction (30 Dec 2016) awarded 68.4 MW of PV; awards of 289 / 514 / 793 MW in 2017 / 2018 / 2019. Total PV ≈1.6 GW by Q1 2020.	Cascade 2014 predates the Act (adopted February 2015); actual simultaneous fulfillment occurs in 2016 when auctions opened and first contracts were awarded.
ROU	Romania	NA	2013	2012	Law 220/2008 Renewable Energy Act, operational from 2011; 6 green certificates/MWh for PV commissioned before end-2013.	Singureni 1 MW (Dec 2010) and Scornicești 1 MW (Dec 2011) preceded the boom. Capacity 761 MW (2013) → 1222 MW (2014); GC support cut Jan 2014.	Cascade 2013 captures the peak. 2012 is the first simultaneous year with policy, multi-MW commissioning, and multi-year sustained growth.
SEN	Senegal	NA	2013	2016	Senegal Electricity Law (1998 amended 2010); CRSE tariff-setting framework and IPP procurement (operational 2013).	Bokhol 20 MW (22 Oct 2016, GreenWish) and Malicounda 22 MW (grid-connected Sep 2016, Solaria). Five utility-scale plants (~122 MW) online by 2019; Scaling Solar (Kael 25 + Kahone 35 MW) followed in 2021.	Cascade 2013 predates commissioning by 3 years. Recalibrate to 2016 as first simultaneous year.
SLV	El Salvador	NA	2016	2017	First renewable energy auction held by Consejo Nacional de Energía (CNE), October 2014; regulatory framework	Providencia 101 MW DC grid-connected 1 Apr 2017 (2014 auction); 2nd auction (Mar 2017) awarded 119.9 MW DC of solar plus 70 MW of wind;	Cascade 2016 predates commissioning. Calibrated to 2017 when Providencia came online, triggering the second auction wave.

Code	Country	FOBI Year	Cascade Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
					operational 2015.	Capela 140 MW DC (2020).	
TUR	Turkey	NA	2014	2014	Renewable Energy Law amendments 2011 (FIT US$133/MWh); License-Exempt Regulation end-2013 (unlicensed ≤1 MW).	First unlicensed (≤1 MW) connections Q3 2014; 600 MW licensed tender bid from May 2014. Capacity 40 MW (2014) → 249 (2015) → 833 (2016) → 3421 (2017) → 5063 (2018), unlicensed-dominated.	Cascade 2014 retained. License-Exempt Regulation plus first unlicensed commissioning and subsequent 5-year acceleration all anchor 2014.
UKR	Ukraine	NA	2012	2011	Green Tariff Law 2008 (Law 601-VI), operational April 2009 with EUR 0.46/kWh FIT; one of the highest in Europe.	Okhotnykovo 80 MW (Oct 2011) and Perovo 100 MW (Dec 2011; then world's largest). Capacity 3 MW (2010) → 188 MW (2011) → 372 MW (2012) → 6225 MW (2020; excl. Crimea post-2014).	Cascade 2012 captures the post-commissioning year. 2011 is the simultaneous year: FIT operational, Europe-leading PV parks online, multi-year expansion begins.
URY	Uruguay	NA	2014	2015	Decree 133/013 (2013) authorizing solar auctions; UTE Plan Solar framework and 15 auctioned PPAs signed 2013–2014.	La Jacinta 64.8 MWp (grid supply Jul 2015; UTE acceptance 7 Sep 2015), first utility-scale plant under the auctioned PPAs. Plateau ≈250 MW by 2018.	Cascade 2014 predates commissioning. Calibrated to 2015 when La Jacinta anchored the PPA-backed pipeline.
VNM	Vietnam	NA	2016	2017	Decision 11/2017/QD-TTg (11 April 2017), FIT of 9.35 US¢/kWh for projects operational by 30 June 2019.	First FIT1 plants from mid-2018; 4.46 GW online by the 30 Jun 2019 deadline. Capacity 8 MW (pre-2017) → 16.7 GW (2020).	Cascade 2016 predates policy. Calibrated to 2017, the Decision 11 year, which triggered the largest annual PV build-out in Southeast Asia.

Code	Country	FOBI Year	Cascade Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
ARE	UAE	2019	2016	2017	UAE Energy Strategy 2050 (January 2017); DEWA Shams Dubai net-metering (2015); Abu Dhabi Mohammed bin Rashid Al Maktoum Solar Park framework.	MBR Phase I 13 MW (22 Oct 2013); Phase II 200 MW (20 Mar 2017); Noor Abu Dhabi 1177 MW (COD 30 Apr 2019). Capacity 35.3 MW (2016) → 2232 MW (2020).	Cascade 2016 captures the DEWA Shams framework; FOBI 2019 captures Noor Abu Dhabi completion. Simultaneous fulfillment occurs in 2017 with DEWA Phase II and Strategy 2050.
AUT	Austria	2010	2019	2010	Ökostromgesetz 2008 and 2012 amendment; Klima- und Energiefonds subsidies for small-scale PV from 2008.	No utility-scale anchor: largest plant 2 MW (2011); first ≥10 MW park Dec 2020 (Schönkirchen 11.4 MWp). Rooftop-led capacity 49 MW (2009) → 89 (2010) → 626 (2013).	FOBI 2010 retained. Cascade 2019 captures the second wave under EAG 2020 preparation; FOBI correctly isolates the Ökostromgesetz-driven onset.
DEU	Germany	2008	2012	2008	EEG 2004 amendment (PV FIT €0.40–€0.57/kWh); EEG 2009 extension with adjusted rates operational January 2009.	Waldpolenz 40 MW and Köthen 45 MW (Dec 2008); Finsterwalde 80.7 MW (2009–10). Capacity 4170 MW (2007) → 6120 (2008) → 10540 (2009) → 18004 (2010) → 25914 (2011).	FOBI 2008 retained. Cascade 2012 captures the peak-year consolidation; 2008 is the first simultaneous year with FIT structural reform plus utility-scale commissioning.
ESP	Spain	2008	2019	2008	Royal Decree 661/2007 (FIT operational May 2007); Royal Decree 1578/2008 (tariff revision September 2008).	Olmedilla 60 MW and Puertollano ~50 MW (2008). Capacity 494 MW (2007) → 3384 MW (2008) → 3423 MW (2009); moratorium 2012; second wave from 2018.	FOBI 2008 retained. Cascade 2019 captures the second-wave onset under the Royal Decree 359/2017 auction regime; 2008 is the first simultaneous year of the original boom.

Code	Country	FOBI Year	Cascade Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
HUN	Hungary	2019	2014	2017	METÁR feed-in premium (Act LXXXVI of 2016), operational January 2017; replaced KÁT scheme.	First large ground-mounted parks 2016–17 (Felsőzsolca, Pécs); prosumer rooftop from 2017. Capacity 235 MW (2016) → 728 (2018) → 1400 (2019) → 2131 (2020).	Cascade 2014 predates utility-scale commissioning. FOBI 2019 captures the METÁR auction outcomes. Calibrated to 2017, the simultaneous year.
MEX	Mexico	2019	2016	2016	Energy Reform 2013; CRE long-term auction framework (first auction March 2016 awarded 1,691 MW solar).	First-auction plants from late 2017; Villanueva 754 MW partial Mar 2018, full COD Sep 2018 (1089 MW with Don José). Capacity 2567 MW (2018) → 6695 MW (2020).	Cascade 2016 retained and calibrated to 2016. FOBI 2019 captures full operation of first-auction plants; 2016 is the first simultaneous year.
PRI	Puerto Rico	2018	2012	2012	Act 82 (2010) and Act 83 (2010) establishing 20% renewable portfolio standard; PREPA net-metering framework from 2011.	AES Ilumina 24 MW (Oct 2012); Oriana 45 MW (Dec 2016). Five utility-scale farms in full operation by mid-2017; ~88 MW distributed via net metering (Jun 2017).	Cascade 2012 retained. FOBI 2018 captures the post-hurricane rebound; 2012 is the original simultaneous year.
PRT	Portugal	2009	2017	2009	Decree-Law 225/2007 setting FIT structure; Moura solar plant PPAs and sector strategy operational from 2008.	Serpa 11 MW (Mar 2007) and Amareleja 45.8 MW (Dec 2008). Capacity 59 MW (2008) → 115 (2009) → 134 (2010) → 172 (2011) → 238 (2012).	FOBI 2009 retained. Cascade 2017 captures the second wave under auctions from 2019; 2009 is the original simultaneous year.

Table S3. Primary sources supporting the calibrated take-off years for solar PV

Notes. URLs accessed April 2026. Where national TSO or ministry sources were not publicly reachable, we cite the most authoritative secondary source (pv magazine, PV-Tech, Windpower Monthly, IRENA, IEA, and regulator-verified project pages), corroborated against at least one independent project registry (Global Energy Monitor, The Wind Power equivalent for solar, or IRENA Renewable Capacity Statistics). All commissioning dates refer to grid-connected commercial operation, not ground-breaking or financial close.

Code	Country	Source Category	Description	URL
BEL	Belgium	Policy / capacity data	TSE / Toulouse School of Economics: political economy of PV subsidies (Flanders GC scheme 2006–2012, capacity trajectory).	https://www.tse-fr.eu/sites/default/files/TSE/documents/doc/wp/2022/wp_tse_1329.pdf
BEL	Belgium	Capacity trajectory	Solarplaza: Belgium 2011 PV market 687 MW; Flanders accounted for 86% of growth.	https://www.solarplaza.com/resource/11212/belgiums-2011-pv-market-beats-previous-record-year/
BEL	Belgium	Policy retrospective	pv magazine: Flanders green-certificate scheme 2009–2013, ~1 GW commercial and 500 MW residential.	https://www.pv-magazine.com/2022/07/25/belgiums-flanders-region-wants-to-retroactively-cancel-green-certificates-for-large-pv-systems/
BGR	Bulgaria	Policy instrument	CMS Expert Guide: Renewable Energy Act 2011; >1 GW PV installed capacity from 2011 onward.	https://cms.law/en/int/expert-guides/cms-expert-guide-to-electricity/bulgaria
BGR	Bulgaria	Capacity trajectory	Enerdata: solar 6 MW (2009) → 212 MW (2011) → >1 GW (2013).	https://www.enerdata.net/publications/daily-energy-news/bulgaria-removes-feed-tariffs-new-renewable-projects.html
BGR	Bulgaria	Policy chronology	Climatescope 2021: Bulgaria FIT evolution and retroactive 2012 cuts.	https://2021.global-climatescope.org/markets/bg/
BOL	Bolivia	Commissioning	pv magazine: Uyuni 60 MW commissioned September 2018 (Bolivia's third large-scale state solar project after Yunchará and Cobija).	https://www.pv-magazine.com/2018/09/10/bolivia-commissions-60-mw-solar-park/

Code	Country	Source Category	Description	URL
BOL	Bolivia	Sector history	Power Technology: Bolivia opens its largest solar farm (Yunchará and Cobija already at 5 MW each).	https://www.power-technology.com/news/bolivia-opens-largest-solar-farm/
BOL	Bolivia	Project profile	Power-Technology profile: Uyuni Solar PV Park commissioned September 2018.	https://www.power-technology.com/data-insights/power-plant-profile-uyuni-solar-pv-park-bolivia/
BRA	Brazil	Policy / auction	ScienceDirect: 6th Reserve Energy Auction October 2014, 31 projects, 889.7 MW AC awarded.	https://www.sciencedirect.com/science/article/abs/pii/S1364032118302132
BRA	Brazil	Capacity trajectory	EnergyTracker: Brazil solar surpassed 55 GW in March 2025, auction-driven.	https://energytracker.asia/solar-energy-in-brazil/
BRA	Brazil	Sector history	Recharge News: Brazil's first commercial 10 MW utility-scale plant; net-metering from 2012, slow uptake 2012–2014.	https://www.rechargenews.com/solar/868316/brazilian-solar-celebrates-historic-new-dawn
CHL	Chile	Commissioning	EnergyTrend: Chile's PV reaches 150 MW after Amanecer (93 MW) and San Andrés (48 MW) commissioning early 2014.	https://www.energytrend.com/news/20140324-6411.html
CHL	Chile	Sector history	ScienceDirect: Tambo Real (2.9 MW, December 2012) first PV plant; 2014 onwards exponential growth.	https://www.sciencedirect.com/science/article/abs/pii/S1364032118303198
CHL	Chile	Capacity trajectory	Solar power in Chile (Wikipedia): multi-GW deployment since 2014; 246 MW El Romero (2016); 8.4 GW by 2023.	https://en.wikipedia.org/wiki/Solar_power_in_Chile
GRC	Greece	Policy instrument	IEA Policies Database: rooftop FIT for ≤10 kWp, June 2009.	https://www.iea.org/policies/4867-feed-in-tariff-for-solar-pv
GRC	Greece	Capacity trajectory	Solar Edition: cumulative 202 MW (2010) → 2,763 MW (2019); boom 2011–2013.	https://solaredition.com/what-made-greece-a-country-with-renewable-energy-potential-solar-in-particular/
GRC	Greece	Sector history	Solar power in Greece (Wikipedia): feed-in tariffs, Law 3851/2010, 9.6 GW by end-	https://en.wikipedia.org/wiki/Solar_power_in_Greece

Code	Country	Source Category	Description	URL
			2024.	
LKA	Sri Lanka	Policy instrument	Sri Lanka Sustainable Energy Authority: Soorya Bala Sangramaya launched 6 September 2016.	https://www.energy.gov.lk/en/renewable-energy/technologies/solar-energy
LKA	Sri Lanka	Policy detail	ESCAP Policy Document Management: Soorya Bala Sangramaya net-metering, net-accounting, net-plus schemes.	https://policy.asiapacificenergy.org/node/3206
LKA	Sri Lanka	Capacity trajectory	ScienceDirect: residential PV uptake since 2016 SBS launch.	https://www.sciencedirect.com/science/article/abs/pii/S0301421518302325
NAM	Namibia	Commissioning	PV Tech: Omburu 4.5 MW construction 2014–2015; first utility-scale PV plant.	https://www.pv-tech.org/namibia_in_line_for_first_large_scale_pv_power_plant/
NAM	Namibia	Policy instrument	MitigationAtlas / GMPA: Interim REFIT scheme commenced April 2015 (14 IPPs × 5 MW).	https://www.dlapiper.com/en-us/insights/publications/2021/11/africa-energy-futures/africa-energy-futures-namibia
NAM	Namibia	Commissioning	Etanga News: Omburu PV Plant inaugurated 13 May 2015 by President Nujoma.	https://etangonam.com/?p=642
NAM	Namibia	Sector trajectory	US Commerce Country Guide: Namibia's first solar plant May 2015; NamPower fleet expansion.	https://www.trade.gov/country-commercial-guides/namibia-energy
POL	Poland	Policy instrument	IEA Policies Database: Renewable Energy Act of Poland (Amended), auctions from December 2016.	https://www.iea.org/policies/5737-renewable-energy-act-of-poland-amended
POL	Poland	Auction outcomes	PubMed Central / Energies 2021: auction volumes 2016–2019 (68, 289, 514, 793 MW).	https://pmc.ncbi.nlm.nih.gov/articles/PMC9477179/

Code	Country	Source Category	Description	URL
POL	Poland	Capacity trajectory	U.S. Dept of Commerce: PV capacity 1,597 MW at March 2020; fourth-largest EU annual addition in 2019.	https://www.trade.gov/market-intelligence/poland-photovoltaics
ROU	Romania	Policy instrument	ScienceDirect: Law 220/2008 Renewable Energy Act, 6 GC/MWh to end-2013, 3 GC/MWh 2014–2016.	https://www.sciencedirect.com/science/article/abs/pii/S2213138822005379
ROU	Romania	Capacity trajectory	pv magazine: Romania +363 MW PV in 2014, cumulative 1,223 MW.	https://www.pv-magazine.com/2015/02/16/romania-installs-363-mw-of-pv-in-2014_100018227
ROU	Romania	Sector history	Solar power in Romania (Wikipedia): Singureni (2010) and Scornicești (2011) first industrial parks; 2013 peak year.	https://en.wikipedia.org/wiki/Solar_power_in_Romania
SEN	Senegal	Commissioning	IFC / Scaling Solar: Kahone and Kael plants commissioned 2021; Senegal is the second Scaling Solar operational country.	https://www.ifc.org/en/pressroom/2021/scaling-solar-two-pv-plants-bring-clean-energy-to-more-than-500000-in-senegal
SEN	Senegal	Sector overview	IEA: Senegal Case Study on utility-scale solar PV and wind.	https://www.iea.org/reports/senegal-case-study/utility-scale-solar-pv-and-wind-in-senegal-overcoming-regional-related-risk-perceptions-with-an-attractive-investment-proposition
SEN	Senegal	Financing	MIGA / World Bank Group: Scaling Solar Senegal, 79 MWp two-plant PPA with Senelec.	https://www.miga.org/project/scaling-solar-senegal
SLV	El Salvador	Commissioning	pv magazine: Neoen commissions 101 MW Providencia facility, connected 1 April 2017.	https://www.pv-magazine.com/2017/05/03/neoen-commissions-101-mw-solar-facility-in-el-salvador/
SLV	El Salvador	Financing	IDB Invest: first-ever utility-scale solar PV (Providencia) financed via IIC.	https://idbinvest.org/en/news-media/iic-finances-first-ever-utility-scale-solar-pv-power-plant-el-salvador
SLV	El Salvador	Project details	AFD / Proparco: La Providencia project page, 100 MWp total (Antares 75 MWp + Spica 25 MWp).	https://www.proparco.fr/en/carte-des-projets/providencia-solar

Code	Country	Source Category	Description	URL
TUR	Turkey	Policy instrument	Norton Rose Fulbright: 2011 FIT; 2013 License-Exempt Regulation; first licensed auction May 2014.	https://www.nortonrosefulbright.com/en/knowledge/publications/4e5c0606/turkey-take-the-winding-road-to-solar-success
TUR	Turkey	Auction history	Ember: YEKA auctions from 2017, 5.8 GW tendered by end-2024.	https://ember-energy.org/latest-insights/new-targets-old-challenges-in-turkish-wind-and-solar-tenders/
TUR	Turkey	Sector trajectory	IEA-PVPS Turkey country page: YEKA 3 GW solar tendered, 1.5 GW operational.	https://ember-energy.org/latest-insights/new-targets-old-challenges-in-turkish-wind-and-solar-tenders/
UKR	Ukraine	Policy instrument	PV Tech: Ukraine FIT EUR 0.46/kWh, 100 MW Perovo Solar Park (2011), fastest-growing Eastern European market.	https://www.pv-tech.org/pv_capacity_in_ukraine_could_reach_500mw_by_the_end_of_2012
UKR	Ukraine	Policy evolution	PV Europe: Ukrainian FIT history and rate adjustments.	https://www.pveurope.eu/solar-modules/feed-tariffs-ukraine-history-dynamics-and-perspectives
UKR	Ukraine	Capacity trajectory	IEA: Ukraine had >9 GW installed PV before 2022 invasion.	https://www.iea.org/reports/policy-options-to-accelerate-distributed-solar-pv-in-ukraine/distributed-solar-pv-in-ukraine
URY	Uruguay	Commissioning	Norton Rose Fulbright: La Jacinta 64.8 MW, first utility-scale project, IDB $ 65.9 million (2014 approval, 2015 commissioning).	https://www.nortonrosefulbright.com/en/knowledge/publications/c7fa4c24/renewable-energy-in-latin-america-uruguay
URY	Uruguay	Sector trajectory	pv magazine Uruguay: UTE tender history and subsequent PV development.	https://www.pv-magazine.com/2019/10/01/uruguay-launches-65-mw-solar-tender/
VNM	Vietnam	Policy instrument	ESCAP Policy Document: Decision 11/2017/QD-TTg issued 11 April 2017.	https://policy.asiapacificenergy.org/node/3446
VNM	Vietnam	Capacity boom	ScienceDirect: Vietnam's solar PV boom 2019, installed capacity reached 4,450 MW by first half of 2019.	https://www.sciencedirect.com/science/article/abs/pii/S0301421520303037
VNM	Vietnam	Sector trajectory	IEEFA: 2018–2023 Vietnam scaled solar + wind from ~0 to 21 GW; PV FIT $ 0.0935/kWh.	https://ieefa.org/resources/boom-balance-vietnams-clean-energy-transition

Code	Country	Source Category	Description	URL
ARE	UAE	Project profile	Solar power in the UAE (Wikipedia): Noor Abu Dhabi 1,177 MW commissioned June 2019.	https://en.wikipedia.org/wiki/Solar_power_in_the_United_Arab_Emirates; https://en.wikipedia.org/wiki/Noor_Abu_Dhabi
ARE	UAE	Policy instrument	UAE Energy Strategy 2050 (adopted January 2017) official government page.	https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/strategies-plans-and-visions/environment-and-energy/uae-energy-strategy-2050
ARE	UAE	Sector overview	IRENA: United Arab Emirates Renewables Readiness Assessment.	https://www.irena.org/-/media/Irena/Files/RRA/RRA_Design_to_Action.pdf?appgw_azwaf_jsc=GQc99edL1k1fzcd14SigTTzTTAoIE3hJStJxBGofzRN8qtH-QvMwMtqq_vd4MEHBQDj9_1rZPEM9d2ji6rOhPgI_VlrI8LDT28dP5PzPKti3pJjN51cREmMwlX3DYiJn9ZFWREm8_AsBleI-K9BHplSNL4SqFkqxkelRLaEbyQAm7ErTwuZ9-TWJjjP6sLPQDxcfnb9zvkT3O3vfTgf_bFBc_bJBSo3v-9L_SvJ6_8IvDEc2l1LReeT_17Or-O5UUbY0FNOVgiMFJR4UltfwLkXpsNMHegyPmaS4N9IS3n4TFQ6uf3saKLd8xC9VRdD_bRJ5ij4FAjGWvBXikvXu4Q
AUT	Austria	Policy instrument	IEA Policies Database: Ökostromgesetz 2008 and 2012 amendment for renewable electricity support.	https://www.reliable-disclosure.org/upload/165-RE-DISSII_Country_Profile_Austria_2015.pdf
AUT	Austria	Sector overview	Solar power in Austria (Wikipedia): deployment history and capacity trajectory.	https://en.wikipedia.org/wiki/Solar_power_in_Austria
DEU	Germany	Policy instrument	German Renewable Energy Sources Act (Wikipedia): EEG 2004, 2009 amendments.	https://en.wikipedia.org/wiki/German_Renewable_Energy_Sources_Act
DEU	Germany	Sector history	Solar power in Germany (Wikipedia): 1 GW reached 2004, FIT-driven boom, 32 GW by 2012.	https://en.wikipedia.org/wiki/Solar_power_in_Germany

Code	Country	Source Category	Description	URL
DEU	Germany	Policy analysis	Congressional Research Service: EU wind and solar electricity policies, Germany and Spain case studies.	https://www.congress.gov/crs-product/R43176
ESP	Spain	Policy history	CRS / Library of Congress: Royal Decree 661/2007 FIT; Spain largest global PV market 2008.	https://www.congress.gov/crs-product/R43176
ESP	Spain	Sector history	Solar power in Spain (Wikipedia): Olmedilla 60 MW (September 2008); 2012 moratorium; 2018 auction restart.	https://en.wikipedia.org/wiki/Solar_power_in_Spain
HUN	Hungary	Policy instrument	IEA Policies Database: Hungary METÁR scheme operational January 2017.	https://www.iea.org/policies?country=Hungary
HUN	Hungary	Sector trajectory	Solar power in Hungary (Wikipedia): KÁT to METÁR transition, 2,131 MW by 2020.	https://en.wikipedia.org/wiki/Solar_power_in_Hungary
MEX	Mexico	Policy instrument	IEA Mexico 2017 Energy Policies Review: Energy Reform 2013, CRE long-term auctions.	https://www.iea.org/reports/energy-policies-beyond-iea-countries-mexico-2017
MEX	Mexico	Auction outcomes	Solar power in Mexico (Wikipedia): first CRE auction March 2016 awarded 1,691 MW solar.	https://en.wikipedia.org/wiki/Solar_power_in_Mexico
MEX	Mexico	Project profile	Villanueva Solar Plant (Wikipedia): 754 MW Enel Green Power plant, COD March 2018.	https://www.enelgreenpower.com/media/news/2018/3/enel-green-power-mexico-inaugurates-villanueva-largest-solar-pv-plant-in-the-americas
PRI	Puerto Rico	Policy instrument	Puerto Rico Act 82-2010 (renewable portfolio standard 12% by 2015, 20% by 2035).	https://www.camarapr.org/presentaciones/Energia-oct2010/Jan_M_Maduro.pdf
PRI	Puerto Rico	Sector history	Solar power in Puerto Rico (Wikipedia): AES Ilumina (24 MW, 2012), Oriana (45 MW, 2013).	https://www.power-technology.com/data-insights/power-plant-profile-aes-ilumina-solar-pv-park-puerto-rico/; https://www.sonnedix.com/news/the-largest-solar-power-plant-in-the-caribbean-begins-producing-energy

Code	Country	Source Category	Description	URL
PRT	Portugal	Project profile	Amareleja Solar Power Plant (Wikipedia): 46 MW commissioned December 2008.	https://www.power-technology.com/data-insights/power-plant-profile-amareleja-solar-park-a-portugal/
PRT	Portugal	Sector history	Solar power in Portugal (Wikipedia): Decree-Law 225/2007 FIT; Serpa (2007), Amareleja (2008); auctions from 2019.	https://www.lexology.com/library/detail.aspx?g=bfd1d07b-4535-44e9-9483-3f7a670fbd95; https://en.wikipedia.org/wiki/Solar_power_in_Portugal
ALL	All countries	Cross-cutting database	IEA Policies and Measures Database (multi-country RES-E policy repository).	https://www.iea.org/policies
ALL	All countries	Cross-cutting database	IRENA Renewable Capacity Statistics (annual installed PV capacity by country).	https://www.irena.org/Publications/2024/Mar/Renewable-capacity-statistics-2024
ALL	All countries	Cross-cutting database	pv magazine archive (project-level commissioning and policy news).	https://www.pv-magazine.com/

Table S4. Historical calibration results of take-off years and supporting evidence for onshore wind

The calibrated year is the earliest calendar year satisfying, simultaneously, an operational enabling policy instrument, at least one commissioned commercial-scale project (≥10 MW grid-connected), and annual capacity additions entering a sustained multi-year expansion (operationalized as ≥3 consecutive years of non-zero additions within the 5 years following the candidate year, or ≥2-fold capacity increase over that window). Countries exhibiting a single commissioned project followed by a plateau exceeding 4 years cannot satisfy criterion 3 and are classified as *no take-off* irrespective of cascade-gated detection.

Code	Country	FOBI Year	Cascade-gated Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
EST	Estonia	NA	2009	2007	Electricity Market Act 2007 (feed-in premium, eligibility ⩽125 MW net capacity, 12-year tenor).	Pakri 18.4 MW (8 turbines) and Esivere 8 MW (4 turbines), both 2005. Capacity 31 MW (2006) → 104 (2009) → 266 (2012); ~200 MW under construction by mid-2009 (108 MW installed June 2009).	All three criteria first coincide in 2007: a ⩾10 MW fleet pre-existed, policy became operational, and sustained expansion began. Cascade 2009 captured visibility, not onset.
HND	Honduras	NA	2011	2011	Decree 70-2007 (Ley de Promoción a la Generación con Recursos Renovables), operational from 2008.	Cerro de Hula 102 MW (51 × Gamesa G87-2.0), COD December 2011 (inaugurated 22 Feb 2012). 102 MW (2012) → 152 MW (2014) → 228.9 MW (2017).	Simultaneous fulfillment at 2011: the first commercial-scale project commissioned under an operational policy, followed by sustained additions.
NIC	Nicaragua	NA	2013	2009	Law 532 (Ley de Promoción de Fuentes Renovables, 2005), operational from 2007.	Amayo I 39.9 MW (19 × Suzlon S88-2.1), March 2009. Amayo II +23.1 MW (2010) → Eolo +44 MW (2013) → La Fe – San Martín (39.6 MW, 22 × V90-1.8) + Alba Rivas (~40 MW), +79 MW to 186 MW by 2014.	Cascade 2013 captures the second wave. Earliest simultaneous year is 2009, when Amayo I anchored the first sustained trajectory under Law 532.

Code	Country	FOBI Year	Cascade-gated Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
PAN	Panama	NA	2014	2014	Law 44 of 2011 (Régimen de Incentivos para Centrales Eólicas), operational from 2012.	Penonómé I (UEP) 55 MW (22 × Goldwind GW2.5), the country's first wind farm; construction from 2012, COD 2014. Penonómé I + II = 270 MW by 2017.	Simultaneous fulfillment at 2014. Three consecutive years of multi-phase commissioning satisfy the sustained-expansion criterion.
CRI	Costa Rica	2014	2000	2014	Seventh ICE Expansion Plan (2012); amended Law 7200 (1995) for IPPs ≤20 MW.	Chiripa 49.5 MW (33 × AW77/1500), July 2014 (inaugurated 15 Nov 2014); Orosi 50 MW (Sep 2015); Tilawind 20 MW (Mar 2015).	The first wave failed criterion 3 (7-year plateau). The second wave satisfies all three at 2014; FOBI correctly isolates the statistically significant transition.
DNK	Denmark	1991	2000	1991	Energy 2000 plan (1990); 100 MW Agreements (first agreed 1985, second commonly dated 1990); statutory purchase at 70–85% of local retail price.	Cooperative and utility onshore expansion under the 100 MW Agreements (first agreed 1985, build-out 1986 – 1990). Total wind capacity 326 MW (1990) → 600 (1995) → 2404 MW (2000).	The first 100 MW Agreement (1985) sat in the formative phase. Simultaneous fulfillment with the sustained-expansion transition occurs under the 1990–1992 policy triad, dated 1991 (the second-agreement '1991' date pending a source). Cascade 2000 captured peak visibility.
IRL	Ireland	2005	2009	2006	REFIT 1 from 1 May 2006; EU state-aid clearance September 2007 (Commission N571/2006).	First REFIT-supported farms from 2007, preceded by AER-backed farms from 1997. Capacity 169 MW (2003) → 744 (end-2006) → 1260 MW by January 2011; REFIT-1 added 1242 MW, reaching ~15% RES-E by 2010.	Re-examine: the 2003–06 ramp (~190 MW/yr) pre-dates REFIT-supported connections and contradicts the '<80 MW/yr formative' premise. Either justify 2006 purely as the policy trigger or test a 2004–05 sensitivity. FOBI 2005 and cascade 2009 bracket the policy onset.

Code	Country	FOBI Year	Cascade-gated Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
LUX	Luxembourg	2013	2001	2013	Grand-Ducal feed-in regulation (2008, revised 2012); Plan National Énergies Renouvelables (2010).	No sourced 2013 anchor: Hengischt has run since 1998 (extensions 2003/2016/2021; 19.56 MW after repowering) and Garnich was built in 2020. Capacity 42 MW (end-2010) → 214 MW (end-2024); wind supplied >25% of generation 2017 – 2022 and ~43% in 2023.	Re-adjudicate: the 2013 anchor is unsourced and the 'pre-2013 sub-MW fleet' premise is falsified. Candidate triggers are the 2008 feed-in regulation or the mid-2010s build/repowering wave.
NZL	New Zealand	2003	2007	2004	Electricity Industry Reform Act (1998); RMA consenting regime (market-driven, no subsidy).	Te Āpiti 90.75 MW, December 2004 — first farm on the national grid and first with >1 MW turbines; Tararua Stage 2 36.3 MW (2004). Capacity 72 MW (2003) → 166 (2004) → 320 (2007) → 623 MW (2011) via White Hill, Tararua Stage 3 (93 MW, Sep 2007), West Wind, and Te Rere Hau (48.5 MW, 2006–2011).	Tararua Stage 1 (1999) plus a 5-year hiatus fails criterion 3. 2004 marks the first year of simultaneous fulfillment; cascade 2007 captures the second wave.
ABW	Aruba	NA	2010	—	2008 WEB Aruba build-own-operate tender; financial close December 2008.	Vader Piet 30 MW (10 × Vestas V90-3.0), December 2009 — the only wind plant. Capacity flat at 30 MW from 2010 through 2024 (⩾14 years); output stable at ~142 GWh/yr (~15% of demand).	Criterion 3 fails. A single-installation step change cannot satisfy sustained multi-year expansion.

Code	Country	FOBI Year	Cascade-gated Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
SOM	Somalia	NA	2014	—	No national RES framework; private mini-grid operators (NECSOM, BECO) only.	Garowe NECSOM/EPS microgrid phase 1 (Feb 2016) was 1 MW solar PV + 1.4 MWh storage, no wind; the 0.75 MW wind component (3 turbines) was added in the 2017 extension. No grid-connected wind; sub-MW mini-grid only.	Criteria 1, 2, and 3 all fail. Cascade 2014 predates any documented wind commissioning.
TCD	Chad	NA	2016	—	ADER mandate, 2015.	Amdjarass 1.1 MW (4 × Vergnet GEV MP 275 kW) turbines erected February 2016, but full hybrid-plant commissioning was repeatedly delayed (a 2022 report targets 2025). No operational utility-scale capacity through 2024.	Criteria 2 and 3 fail. A sub-utility installation with no trajectory.
VUT	Vanuatu	NA	2009	—	National Energy Policy Framework (2007); EIB finance contract September 2009.	Devil's Point commissioned October 2008 with 11 Vergnet turbines (3025 kVA); the EIB-financed 2.75 MW extension (contract Sep 2009) expanded that existing fleet. Current fleet 3.4 MW (12 × GEV MP + one 100 kW XANT); static since.	Criterion 3 fails. A single-project small-island regime with no formative-to-acceleration transition.

Code	Country	FOBI Year	Cascade-gated Year	Calibrated Year	Anchoring Policy	Commissioning & Expansion	Adjudication
MKD	North Macedonia	NA	2014	—	Energy Law 2011; feed-in tariff regulation for wind.	Bogdanci Phase I 36.8 MW (16 × Siemens SWT-2.3-93), grid-connected end-March 2014. 7-year plateau 2014–2020; Bogoslovec 36 MW (first private farm) completed 2023, not 2021; Bogdanci Phase II 13.8 MW planned.	Criterion 3 fails 2014 – 2020. The provisional year moves 2021 → 2023 (Bogoslovec completion); confirm sustained additions post-2023.
MRT	Mauritania	NA	2013	—	National Electricity Code (2011); Arab Fund for Economic and Social Development co-financing (2013).	Nouakchott 30 MW (15 × Gamesa G97-2.0), first operation 1 July 2015, commissioned November 2015. Boulenouar 102 MW (39 × 2.625 MW) commissioned December 2023, not 2020 — an eight-year gap to the second project.	Cascade 2013 predates any commissioning and is rejected. 2015 is the earliest simultaneous year; the 8-year expansion gap (2015→2023) reinforces the sustainability-borderline verdict.

Table S5. Primary sources supporting the calibrated take-off years for onshore wind

URLs accessed April 2026. Where a national TSO or ministry source was not publicly reachable, we cite the most authoritative secondary source (Windpower Monthly, Power-Technology, ACCIONA, Meridian Energy, Globeleq, Goldwind) corroborated against at least one independent project registry (The Wind Power, Global Energy Monitor, or IRENA Renewable Capacity Statistics). All commissioning dates refer to grid-connected commercial operation, not ground-breaking or financial close.

Code	Country	Source Category	Description	URL
ABW	Aruba	Commissioning	Vader Piet Wind Farm official operator page, commissioning December 2009, 30 MW.	https://www.windparkvaderpiet.com/
ABW	Aruba	Commissioning	Vader Piet Wind Farm (Wikipedia), first wind farm in Aruba, commissioned December 2009.	https://en.wikipedia.org/wiki/Vader_Piet_Wind_Farm
ABW	Aruba	Project profile	Power-Technology profile: 30 MW, Vestas V90-3.0 MW, commissioned December 2009.	https://www.power-technology.com/data-insights/power-plant-profile-vader-piet-aruba/
ABW	Aruba	Policy / tender	South Pole project documentation: 2008 WEB Aruba BOO tender, financing December 2008.	https://www.southpole.com/uploads/media/1938.pdf
SOM	Somalia	Commissioning	Garowe hybrid solar–wind plant, operational from 22 February 2016.	https://www.lifegate.com/somalia-garowe-solar-wind-hybrid-plant
SOM	Somalia	Sector overview	U.S. Dept. of Commerce Country Commercial Guide: no national RES framework; Garowe 3.5 MW hybrid plant.	https://www.trade.gov/country-commercial-guides/somalia-energy-and-electricity
TCD	Chad	Commissioning	Windpower Monthly: Amdjarass 1.1 MW wind farm commissioned 2016; Chad's first large-scale wind farm targeted for 2025.	https://www.windpowermonthly.com/article/1788093/chads-first-large-scale-wind-farm-could-deliver-first-power-2025
TCD	Chad	Commissioning	REVE / evwind: Amdjarass 1.1 MW commissioned 2016; N'Djamena 100 MW planned 2025/26.	https://evwind.aeeolica.org/?p=86336

Code	Country	Source Category	Description	URL
VUT	Vanuatu	Commissioning	European Investment Bank: Devil’s Point Wind Farm commissioned end of 2008.	https://prdrse4all.spc.int/sites/default/files/prif-re-web_2.pdf
VUT	Vanuatu	Financing	EIB press release 2009-183: EUR 4.3 million loan for 2.75 MW wind farm on Efate.	https://eib.org/en/press/all/2009-183-the-european-investment-bank-provides-650-million-vatu-for-renewable-energy-in-vanuatu
VUT	Vanuatu	Operator data	UNELCO Engie: Devil's Point 3 MW wind farm generates ~9% of Port-Vila power.	https://www.unelco.engie.com/en/commitments/objectives-on-renewable-energy/wind-power
MKD	North Macedonia	Commissioning	WBIF: Bogdanci Phase I (36.8 MW) completed March 2014; Phase II ongoing.	https://www.wbif.eu/10-years-success-stories/success-stories/north-macedonia-plugs-greener-future-through-wind-power
MKD	North Macedonia	Commissioning	WeBalkans / EU: Bogdanci 36.8 MW completed 2014, ~112 GWh yr^{-1}.	https://webalkans.eu/en/stories/winds-of-change-for-north-macedonias-energy-production/
MKD	North Macedonia	Second wave	CEENERGYNEWS: Bogdanci Phase II (15 MW) agreement with Siemens Gamesa, 2023.	https://ceenergynews.com/renewables/north-macedonias-flagship-wind-project-enters-its-final-phase/
MKD	North Macedonia	Project details	REVE: 36.8 MW Bogdanci wind farm with 16 Siemens turbines, construction completed February 2014.	https://evwind.aeeolica.org/2015/07/07/wind-energy-in-macedonia-36-8-mw-bogdanci-wind-farm-with-16-siemens-wind-turbines/53213
EST	Estonia	Policy instrument	IEA Policies Database: Electricity Market Act, Estonia feed-in premium, 2007.	https://www.iea.org/policies/6548-electricity-market-act-estonia-feed-in-premium
EST	Estonia	Commissioning history	ERR News: Virtsu I (2002), Pakri and Esivere (2005), rapid additions from 2007 onward.	https://news.err.ee/1609071998/dozens-more-wind-turbines-to-be-added-to-estonia-s-150-in-next-few-years

Code	Country	Source Category	Description	URL
EST	Estonia	Sector context	Estonian Environmental Portal: chronological overview of Estonian wind farms.	https://keskkonnaportaal.ee/en/topics/renewable-energy/wind-power
EST	Estonia	Capacity trajectory	Wind power in Estonia (Wikipedia): ~694 MW installed as of 2024.	https://en.wikipedia.org/wiki/Wind_power_in_Estonia
HND	Honduras	Commissioning	PR Newswire / Globeleq: Cerro de Hula 102 MW, commercial operation December 2011.	https://www.prnewswire.com/news-releases/honduras-celebrates-wind-energy-140271633.html
HND	Honduras	Project details	CleanTechnica: Gamesa/Iberdrola bring 102 MW Cerro de Hula online.	https://cleantechnica.com/2012/02/22/gamesa-iberdrola-bring-central-americas-largest-wind-farm-online/
HND	Honduras	Sector context	Renewable energy in Honduras (Wikipedia): 100 MW wind built in 2012; Decree 70-2007 incentives.	https://en.wikipedia.org/wiki/Renewable_energy_in_Honduras
NIC	Nicaragua	Commissioning	Renewable Energy World: Amayo I (40 MW) online early 2009; Amayo II (23 MW) April 2010.	https://www.renewableenergyworld.com/wind-power/arctas-sells-nicaraguan-wind-farms-to-aei/
NIC	Nicaragua	Policy instrument	EBSCO Research Starters: Law 532 Renewable Energy Promotion Law (2005); Amayo online 2009.	https://www.ebsco.com/research-starters/power-and-energy/nicaraguas-privatized-energy-system
PAN	Panama	Commissioning / financing	PR Newswire / Goldwind: 55 MW Penonomé Phase I financing closed August 2013; operation 2014.	https://www.prnewswire.com/news-releases/goldwind-usa-inc-closes-financing-for-55mw-penonome-wind-farm-218369951.html
PAN	Panama	Commissioning	GTR: Penonomé 220 MW online in 2014, Panama's first wind farm.	https://www.gtreview.com/news/americas/wind-farm-first-for-panama-2/
PAN	Panama	Project profile	Power-Technology profile: 270 MW Penonomé wind farm, commercial operation 2014.	https://www.power-technology.com/data-insights/power-plant-profile-penonome-wind-farm-panama/

Code	Country	Source Category	Description	URL
PAN	Panama	Operator data	Goldwind Americas: Penonomé I+II, 270 MW, 86 Goldwind 2.5 MW turbines.	https://www.goldwindamericas.com/penonome-panamas-foray-wind-energy
MRT	Mauritania	Commissioning	Windpower Monthly: Mauritania's first wind farm (Nouakchott 30 MW) operational mid-2014/2015.	https://www.windpowermonthly.com/article/1219900/mauritania-gets-its-first-wind-farm
MRT	Mauritania	Commissioning	Mauritania Energy: Nouakchott wind farm commissioned November 2015, 15 × Gamesa G97-2.0 MW.	https://www.power-technology.com/data-insights/power-plant-profile-nouakchott-wind-farm-mauritania/
MRT	Mauritania	Operating data	Yacht Carbon Offset project page: Nouakchott plant started operations January 2016, 30 MW.	https://yachtcarbonoffset.com/projects/mauritania-wind-power/
CRI	Costa Rica	Second-wave commissioning	ACCIONA: Chiripa wind farm grid-connected 2014, 49.5 MW, published 16 July 2014.	https://www.rechargenews.com/wind/acciona-adds-49-5mw-in-costa-rica/1-1-864682
CRI	Costa Rica	Project profile	Power-Technology profile: Chiripa commissioned July 2014.	https://www.power-technology.com/data-insights/power-plant-profile-chiripa-costa-rica/
CRI	Costa Rica	Commissioning	Power-Technology profile: Orosi 50 MW commissioned September 2015.	https://www.power-technology.com/data-insights/power-plant-profile-orosi-wind-farm-costa-rica/
CRI	Costa Rica	Sector history	Renewable energy in Costa Rica (Wikipedia): first three private wind plants 1996–1999; Tejona 2002.	https://en.wikipedia.org/wiki/Renewable_energy_in_Costa_Rica
CRI	Costa Rica	Sector history	AWEA Blog: Tejona operational since 2003; Guanacaste (2009); 400+ MW total.	https://www.aweablog.org/how-costa-ricas-volcanoes-could-power-the-countrys-wind-energy-future/
DNK	Denmark	Policy / history	IRENA / GWEC: 30 Years of Policies for Wind Energy: Lessons from Denmark.	https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2013/GWEC/GWEC_Denmark.pdf
DNK	Denmark	Policy instrument	UNESCAP: Denmark's renewable energy policies (Energy 2000, 1,000 MW target).	https://www.unescap.org/sites/default/files/16.%20CS-Denmark-renewable-energy-policies.pdf

Code	Country	Source Category	Description	URL
DNK	Denmark	Policy chronology	Wind power in Denmark (Wikipedia): 1981 energy plan, 1985 nuclear rejection, Energy 2000, Second 100 MW Agreement.	https://en.wikipedia.org/wiki/Wind_power_in_Denmark
DNK	Denmark	Academic / policy history	Oxford Academic: Success of Danish wind energy innovation policy (100 MW agreements 1986, 1991, 1996).	https://academic.oup.com/book/44441/chapter/376662269
DNK	Denmark	Case study	UNFCCC TEC: Wind Energy in Denmark — case study of Energy 2000 and subsequent agreements.	https://unfccc.int/ttclear/misc_/StaticFiles/gnwoerk_static/TEC_NSI/63eb6ced5b1e43429a6eccdef95ff61e/85bd141304c5486fb7f2ef71f8d2d45f.pdf
IRL	Ireland	Policy instrument	ScienceDirect / ESRI: REFIT initiated 1 May 2006; supports 400 MW toward 1,450 MW 2010 target.	https://www.sciencedirect.com/science/article/abs/pii/S0301421511004800
IRL	Ireland	Policy chronology	Ireland 2050: Bellacorick 1992; AER 1995–2005; REFIT 2006.	https://irelandenergy2050.ie/past/renewable-energy/
IRL	Ireland	Capacity trajectory	RTÉ News: Ireland crossed 1,000 MW in 2009 and ~1,400 MW by 2010 with REFIT.	https://www.rte.ie/news/2022/0103/1269242-wind-energy/
IRL	Ireland	Sector context	Wind power in Ireland (Wikipedia): competitive auctions (AER) from 1996 and REFIT 2006–2015.	https://en.wikipedia.org/wiki/Wind_power_in_Ireland
IRL	Ireland	Official statement	Oireachtas Debates: REFIT announced 2006, state-aid clearance 2007; 860 MW RES online July 2006.	https://www.oireachtas.ie/en/debates/question/2011-09-21/81/
LUX	Luxembourg	Policy instrument	Guichet.lu: feed-in tariff and market premium regime for RES-E.	https://guichet.public.lu/en/entreprises/urbanisme-environnement/energie/production-energie/production-electricite-energies-renouvelables.html
LUX	Luxembourg	Policy review	IEA Luxembourg 2020 energy policy review: FIT, premium tariffs, investment subsidies.	https://www.iea.org/reports/luxembourg-2020

Code	Country	Source Category	Description	URL
LUX	Luxembourg	Sector overview	Energy in Luxembourg (Wikipedia): renewables produce 80% of electricity by 2021; wind 26%.	https://en.wikipedia.org/wiki/Renewable_energy_in_Luxembourg
NZL	New Zealand	Commissioning	Meridian Energy: Te Āpiti fully operational 2004; 90.75 MW.	https://www.meridianenergy.co.nz/power-stations/wind/te-apiti
NZL	New Zealand	Commissioning	Te Āpiti Wind Farm (Wikipedia): commissioned 2004; NZ's largest until 2007.	https://en.wikipedia.org/wiki/Te_%C4%80piti_Wind_Farm
NZL	New Zealand	Project profile	Power-Technology: Te Apiti commercial operation December 2004.	https://www.power-technology.com/data-insights/power-plant-profile-te-apiti-new-zealand/
NZL	New Zealand	Commissioning	Tararua Wind Farm (Wikipedia): Stage 1 1999; Stage 2 2004; Stage 3 2007.	https://en.wikipedia.org/wiki/Tararua_Wind_Farm
NZL	New Zealand	Sector history	NZ Geographic: 'Blowin' in the wind' — Tararua Stage 2 in 2004; Te Āpiti opened 2004.	https://www.nzgeo.com/stories/blowin-in-the-wind/
NZL	New Zealand	Encyclopedia	Te Ara Encyclopedia of New Zealand: wind energy overview.	https://teara.govt.nz/en/wind-and-solar-power/page-2
ALL	All countries	Cross-cutting database	IEA Policies and Measures Database (multi-country RES-E policy repository).	https://www.iea.org/policies
ALL	All countries	Cross-cutting database	IRENA Renewable Capacity Statistics (annual installed capacity by technology and country).	https://www.irena.org/Publications/2024/Mar/Renewable-capacity-statistics-2024
ALL	All countries	Cross-cutting database	The Wind Power: global wind farm registry (project-level commissioning and turbine data).	https://www.thewindpower.net/

Table S6. Threshold values for stratification and deployment regimes

Dimension	Metric	Solar PV	Onshore Wind
Annual Deployment	Minimum Scale Threshold	10.3 MW	28.0 MW
Investment Cost	High threshold	2421 $/kW	2099 $/kW
	Low threshold	4131 $/kW	2663 $/kW
Cumulative Capacity	Elite's Scale Threshold	350 MW	500 MW
Penetration	High threshold	2.1%	4.1%
	Low threshold	7.3%	14.1%

Table S7. Summary of physical constraints and boundary parameters applied to the C-SPDM

Parameter Category	Specific Constraint	Solar PV	Onshore Wind
Cost Limits	Cost Floor (C_{floor})	150 $/kW	600 $/kW
Penetration	Penetration Ceiling	1.00	1.00
Learning Rate	LR Floor (LR_{min})	0.05	0.02
	LR Ceiling (LR_{max})	0.35	0.30
Growth Ceiling (by Stage)	Formative Phase	1.00	1.00
	Early Adoption	0.80	0.80
	Cost Parity	0.60	0.60
	Policy-Driven Scaling	0.50	0.50
	Accelerating Growth	0.30	0.30
	Mature Penetration	0.15	0.15

Note: LR denotes Learning Rate.

Table S8. Divergences in Monte Carlo projection between solar PV and onshore wind

Dimension	Solar PV	Onshore wind
Developmental paths	A, B, C, D (four paths retained)	A, B/C, D (Paths B and C merged)
LR aggregation	Path × Stage (Tier 1) → Path (Tier 2) → Global (Tier 3)	Path (Tier 2) → Global (Tier 3); stage tier dropped
Growth aggregation	Path × Stage → Path → Global	Path × Stage → Path → Global
Penetration aggregation	Path × Stage → Path → Global	Path × Stage → Path → Global
Hardware cost floor	150 $/kW	600 $/kW
Learning-rate band	5%–35%	2%–30%
High-penetration threshold	7.3%	14.1%
Elite cumulative capacity	350535 kW	500000 kW
Low-cost threshold	2421 $/kW	2099 $/kW
“Successful” benchmark paths	Paths A, B, C	Paths A, B/C
Laggard scenario label	Leapfrog Learning	Late-Mover Emulation

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