JSER

Journal of Solar Energy Research (JSER)

Journal homepage: www.jser.ut.ac.ir

An Outcome-Based Coupling–Efficiency Framework for Evaluating Solar Expansion Performance

Ankur Gupta*, Ruchika Kulshrestha

Institute of Business Management, GLA University, Mathura, India

ARTICLE INFO

Article Type:

Research Article

Received:2026.02.09
Accepted in revised form:2026.09.10

Keywords:
Solar energy transition; Renewable energy policy; Policy effectiveness; Sustainable energy systems; Coupling–efficiency regimes

A B S T R A C T

Traditional measures of solar energy transitions primarily focus on investment growth and installed capacity rather than on whether policy-driven implementation delivers meaningful energy outcomes. This study provides an analytical approach for assessing solar energy expansion by focusing on realized outcomes rather than capacity growth alone. It examines the relationships among investment behaviour, policy signals, technology adoption, and deployment efficiency. The research offers two indicators, PIACI (Policy_Investment_Adoption_Coupling_Index) and CESA (Carbon_Efficiency_of_Solar_Adoption) based on cross-country panel data on 2010-2023 collected on a global energy and policy database. These metrics reflect both the effectiveness with which energy is produced, as well as the consistency of policy-based growth. The findings reveal substantial differences in national transition pathways through performance-regime analysis and the assessment of regime shifts. The findings indicate that moderate but stable coupling can prove more effective than aggressive but volatile expansion strategies and that strong policy coupling does not necessarily ensure efficient performance. The proposed framework will take renewable energy evaluation to a new level by combining the concepts of coupling, efficiency, and time dynamics to offer an effective instrument of evidence-based solar policy development.

1. Introduction

The global transition toward renewable energy has increased due to growing concerns regarding sustainability, energy security, and climate mitigation. Due to its scale, cost, and ability to adapt to different socioeconomic conditions, solar energy has become an important part of decarbonization efforts among renewable technologies. The dramatic gaps between the policy ambitions, investment patterns, execution results and the real effectiveness of the provided energy services continue to be highly

*Corresponding Author Email: phdglaankur@gmail.com

Cite this article: Gupta, A., & Kulshrestha, R. (2026). An Outcome-Based Coupling–Efficiency Framework for Evaluating Solar Expansion Performance. Journal of Solar Energy Research, 11(3), 3267-3284. https://doi.org/10.22059/jser.2026.410866.1717

DOI: 10.22059/jser.2026.410866.1717

problematic issues of how renewable transitions are considered and operated, even though the installed capacity is growing fast [1].

The history of energy development and climate adaptation indicates that effective outcomes are generally achieved through a combination of institutional, economic, and technical processes rather than through a single policy initiative [2]. Access and sustainability of energy studies also point towards the influence of the institutional capacity and social capital on the long-term results. It implies that effective transitions involve systemic harmonization of conditions along with the implementation of certain policy instruments [3, 4]. Although formal access to energy has improved, households may still experience the consequences of inadequate system integration, including higher costs and unreliable supply [5].

These findings highlight the limitations of conventional evaluation approaches that primarily rely on capacity-oriented indicators [6]. Much of the existing literature measures the performance of renewable energy systems based on narrow, unidimensional measures, including installed generation capacity, amount invested, or estimates of emission reduction. Although these measures are helpful, they provide a very limited perspective and often disregard the functionality of these systems in actual practice [7]. Despite the fact that bibliometric and macro-level analysis can give important system-wide information [8], they do not always capture the dynamic nature of investment and deployment with the change in the policy signal [9]. Consequently, existing assessment methodologies have limited ability to explain why solar transitions remain stable in some countries but stagnate in others despite similar policy measures [10]. Only recent developments in the area of infrastructure and governance studies have underscored the fact that the performance of a system is dependent upon the coordination of the processes of institutional and operational deployment [11]. Nevertheless, empirical approaches capable of jointly assessing deployment alignment, policy responsiveness, and efficiency performance in solar transitions remain limited [12].

Most of the literature to date in print continues to adopt unidimensional measures such as capacity growth or investment expansion to measure renewable transitions even though greater attention is increasingly being paid to such processes. These indicators are informative yet seldom reflect the change in policy efficiency or responsiveness over the time. Due to this, methods of analysis that can simultaneously study the efficiency of deployments and the policy-investment-adoption correlation are still unavailable.

This study addresses the existing gap by providing an integrated analytical framework that simultaneously examines capacity growth, investment patterns, policy responsiveness and efficiency outcomes, in only one empirical framework. The paradigm provides an in-depth understanding of the performance of renewable energy by shifting the emphasis towards the conventional capacity-based indicators.

In response to this limitation, the study introduces an outcome-oriented approach to analyze solar energy transitions. The main objectives are as follows:

1. Develop PIACI to evaluate the interaction among policy signals, investment patterns, and capacity expansion.
2. Establish CESA to assess the efficiency with which installed capacity and investment are translated into actual solar energy production.
3. Identify structural variations and transition patterns by classifying country–year observations into coupling–efficiency regimes.
4. Examine temporal dynamics and regime stability to identify high-performing transition pathways and persistent inefficiencies.

The framework enriches renewable energy policy research with empirical insights and facilitates better policy formulation by jointly examining alignment mechanisms and efficiency outcomes in solar development. The principal contributions of the study are summarized as follows:

- Methodological: PIACI emerged as a dynamic and data-intensive index gauging the effectiveness of policy signals into coordinated investment and capacity growth.
- Efficiency-oriented: CESA was developed to assess how efficiently solar deployment is translated into actual energy production rather than evaluating deployment scale alone.
- Analytical: Establishment of a framework of a coupling-efficiency regime that uncovers

lost efficiencies, uncovers discrepancies, and identifies multiple national pathways.

- Policy relevance: The ability to have a diagnostic tool to assist decision-makers in detecting early inefficiencies and more effectively organize solar energy transition plans.

The literature is starting to identify renewable energy transitions as a coordinated socio-technical process that is influenced by institutional coordination, investor behavior, and infrastructural preparedness. Empirical research indicates that policy efficacy is mediated by supplementing institutional and operational factors as opposed to individual initiatives. The results highlight the importance of assessment systems that look at the coordinated performance of the system as opposed to capacity-based measures.

The study presents the methodological enhancements realized in general equilibrium model GEM-E3-FIT (including enhanced energy system representation, low-carbon innovation, clean energy markets, technology progress, policy instruments) to improve the simulation of the impacts of ambitious climate policies. The inter-dependency of renewable energy transitions as socio technical processes, which are orchestrated through institutional, socioeconomic, and infrastructural coordination as opposed to possibly distinct policy efforts are starting to be understood in current literature [13]. As has been established, to facilitate the results of deployment and long-term adaptability to the system, institutional complementarity, governance capacity, and the availability of information are required [1, 13]. The formal access is not an adequate criterion in identifying the efficient energy consumption in that the dependability, affordability, and institutional trust significantly influence the effects of welfare and service consistency, based on the evidence of energy poverty and household transformation [14]. The integration of infrastructure with the socio-cultural and service settings determines its success, according to development-based research, which supports the need for outcome-based evaluation techniques [9, 15].

In order to guarantee resilience in high-renewable environments, renewable energy governance at the system level entails a unified legislative framework, institutional uniformity, and operational coordination [16, 17]. Structural and geographical variability further indicates that deployment outcomes can differ substantially across national settings because of differences in institutional preparedness and system-integration capacity [18, 19]. Moreover, the analysis of macroeconomic and sustainability reveals that efficiency, structure of composition, and consumption, along with the level of growth, may affect the payoff of decreasing emissions and generating employment [20]. The study uses cross-sectionally augmented distributed lag (CS-ARDL), augmented mean group (AMG), common correlated effects mean group (CCEMG) and the regularized common correlated estimation (rCCE) to show that energy transition and energy transformation reduce energy security risks, while climate change, trade openness and financial market development exacerbate energy challenges. Several studies highlight the growing significance of renewable energy transition and incentive-based approaches in enhancing energy security and sustainability in the long term. Several recent findings suggest that renewable energy investment can play an important role in minimizing energy security risks in major energy consumers [21, 22]. The findings reveal that income inequality significantly and negatively affects renewable energy consumption, suggesting that higher inequality may hinder Italy's transition to clean energy. Therefore, decentralized renewable energy systems have been recognized as efficient ways to enhance energy security through sustainable and equal access to energy. Another significant finding suggests that the government and socio-economic aspects like income inequality play an important role in shaping renewable energy transition [23, 24].

Moreover, recent studies highlight the behavioral and social consequences of unreliable energy systems and underline the fact that resilience is a situational structural process that is not solely affected by technological progress [5, 25].

In conclusion, even if the usage of renewable energy has greatly increased, present analysis techniques have not been thoroughly established and are primarily capacity-based. Integrated empirical models capable of jointly assessing policy responsiveness, investment behaviour, and deployment efficiency are therefore still needed to gain a better understanding of long-term transition performance.

2. Materials and Methods

A quantitative panel-data approach is employed to examine the relationship between renewable-energy policy signals, solar deployment, and realized efficiency outcomes. It is based on actual implementation data, including aspects of policy actions, investment flows, installed capacity, energy production and employment effects, as opposed to perception-based indicators or survey-based measures of adoption. The methodological design follows an outcome-based approach and focuses on evaluating the relationship between policy commitment and efficiency outcomes.

The outcome-focused analytical approach presented in Figure 1 illustrates that strong solar expansion does not necessarily correspond to superior performance. The framework combines the data on capacity expansion, investment patterns, and policy response of multiple sources of renewable energy data, producing PIACI (dimensionless index, range 0–1). The efficiency level of a system is also assessed using CESA (a dimensionless efficiency index ranging from 0–1), which relates installed capacity to actual energy output. The cooperative PIACI CESA test allows the regime to categorize the national solar transition paths, determine trends of structural compatibility and stability, and identify best practices. The strategy will offer evidence-based policy formulation of solar energy and a diagnostic foundation to determine wasteful growth pathways. The overall analytical process comprises four steps as follows:

- Building of a unified country-year solar energy panel database.
- Analysing how deployment dynamics and policy responsiveness interact.
- Creating efficiency and coupling metrics (PIACI and CESA). Comparative diagnostic and regime-based classification

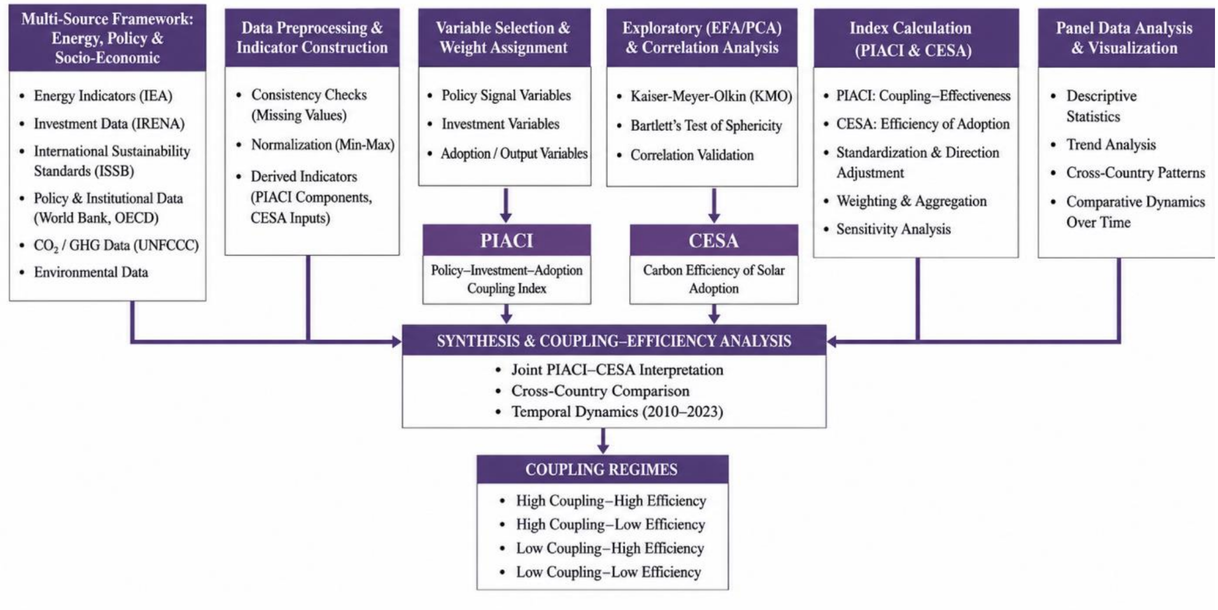

Figure 1. Analytic model of detecting coupling-efficiency mismatches in solar energy growth

This section details the first two steps of the analytical approach. To ensure transparency and ease of replication, variables are indexed using country i and time t. Accordingly, C_{it} captures installed capacity (MW), Q_{it} measures renewable energy share (%), E_{it} reflects employment levels, G_{it} represents solar energy generation (MWh), and I_{it} denotes renewable energy investment (USD). Each indicator is constructed using these observed country–year variables. The overall indices are grounded in actual deployment outcomes rather than planned or intended targets, with year-to-year dynamics evaluated across ordered national panel data.

The empirical analysis will be based on the synthesized data on renewable energy all over the world (including the years 2010-2023). This information will be developed with the help of some credible national and international sources. Data harmonization ensures continuity of data over time and across countries by compiling policy information with observable deployment and economic data.

Primary Data Sources - The following pieces of information are combined to make up the dataset:

- Data on renewable energy output and capacity from the International Energy Agency (IEA).
- Energy shares, employment measures, and investment flows, World Bank.
- Sustainability and environmental indicators of the United Nations Environment Programme (UNEP).
- Data on technology implementation is available at the National Renewable Energy Laboratory (NREL).
- The policy actions and the modifications in regulations, national and government energy reports.

They provide a strong empirical resource base of cross-national comparison and are often applied in policy and transition studies of renewable energy.

Dataset Structure:

Table 1 summarizes the key characteristics of the solar-related and socioeconomic variables used in the study. The data are normalized and scaled using logarithmic transformation before constructing the indices due to noticeable variations in the scale of energy output, financial investment, and installed capacity variables.

The enormous dataset includes nation, year, energy and source panels and consists of more than 500 observations as well as ten factors, which are believed to be vital to the adoption of renewable energy. The data used is restricted to solar energy indicators to achieve analytical accuracy to take more technology-specific trends into account.

The dataset consists of 140 country–year observations over a 14-year period. It covers ten major economies: Australia, Brazil, Canada, China, France, Germany, India, Japan, the United Kingdom, and the United States. The information enables one to have a more realistic evaluation of the effectiveness of the policies because it reflects real performance of deployments instead of the expected performance. Consistency and availability of data in terms of solar related investment, capacity and production measures were considered when selecting the countries. Both the early and mature stages of solar development are also provided in the panel that spans the years 2010-2023, and cross-national and cross-temporal comparisons can be made.

Table 1. Statistical overview of solar energy variables (country–year data)

Variable	obs.	Average	Variability	Min	P25	Median	P75	Max
Energy_Production_MWh	40	1.21×10^8	4.06×10^7	5.02×10^7	8.81×10^7	1.17×10^8	1.60×10^8	1.99×10^8
Investment_in_Renewable_Infrastructure_USD	40	4.94×10^{10}	1.83×10^{10}	2.01×10^{10}	3.19×10^{10}	4.83×10^{10}	6.58×10^{10}	7.89×10^{10}
Installed_Capacity_MW	40	5.45×10^4	2.52×10^4	1.05×10^4	3.26×10^4	5.33×10^4	7.53×10^4	9.92×10^4
Renewable_Energy_Share_pct	40	27.70	13.12	5.18	15.74	28.97	38.83	49.59
Jobs_Created	40	1.83×10^5	6.94×10^4	5.71×10^4	1.23×10^5	1.82×10^5	2.41×10^5	3.00×10^5

(Note: The variable Environmental_Impact_CO2_Reduction contains incomplete entries and is excluded from further analysis.)

Data Preparation and Variable Alignment

A thorough preprocessing process was used to be consistent throughout the dataset. Data Cleaning and Standardization:

All relevant numerical variables—including investment levels, capacity measures, energy generation, and employment—were expressed in consistent units. Records containing missing or invalid values were removed to ensure reliability of the analysis. To ensure consistency, all relevant numerical indicators were converted into comparable units, and records with incomplete or undefined values were filtered out. To identify policy presence and continuity, textual descriptions of policy actions were retained for coding, while sentiment-based or Keynesian-style analysis was not performed. All derived indicators were constructed only from observed data, with no imputation applied. Country-year observations missing core deployment variables were excluded. Although the dataset contains an environmental impact or CO2 reduction field, it was not included in the empirical analysis because the solar-specific observations for that variable were missing or non-informative. Instead, actual solar electricity generation was used as the proxy for deployment efficiency, as it directly reflects the amount of fossil-fuel electricity that solar generation can potentially displace, consistent with established energy-transition research.

Solar-Specific Panel Extraction

To ensure consistency, the analysis focuses exclusively on solar-related data, given that different renewable technologies exhibit distinct policy responses and deployment behaviours. This modification can increase comparability and will enable the improved examination of the linkage between policy, investment and adoption within the solar industry. The i is the index of country and t is the time in this case. The principal variables characterizing solar-energy deployment include installed capacity, energy generation, investment, and related transition indicators, consistent with previous energy-system and renewable-transition studies [11, 21, 23]. The variables used in this study are defined as follows:

$$Prod_{i,t} = \text{Solar energy production (MWh)}$$
$$Inv_{i,t} = \text{Investment in renewable infrastructure (USD)}$$
$$Cap_{i,t} = \text{Installed solar capacity (MW)} \quad (1)$$

Temporal Alignment

The panel in each country was sequenced in a chronological manner to enable dynamic changes to be considered as opposed to just the level of the parameter. This order assists in computing the changes in investment and capacity every year that will be required in the future to couple and analyse efficiency. All the dynamic patterns are computed using observed values; no smoothing was done or trend was adjusted.

Deployment and Policy Responsiveness Signal Extraction

Basic binary measures that merely indicate the presence or absence of policy instruments are not enough to gauge policy responsiveness. These indicators do not represent continuity, persistence or responsiveness, which are the essence of the behavior of long-term investment and deployment outcomes. To address this limitation, the study defines policy impact through a policy-responsiveness component derived from observed deployment response rather than from normative policy categories.

Let $Policy_{i,t}$ indicate whether a country has a solar-related policy action in year t. Because renewable-energy deployment is influenced by the continuity of policy support and investment responses [21, 23], policy responsiveness in this study is designed to reflect both current policy activity and its persistence over time. The policy responsiveness indicator is expressed as:

$$PR_{i,t} = Policy_{i,t} \times Persistence_{i,t} \quad (2)$$

where $Persistence_{(i,t)}$ reflects whether policy actions are maintained over successive years. This formulation places greater emphasis on continuity in policy implementation rather than isolated or short-term measures. To allow comparison across countries and time periods, the responsiveness measure is transformed to the unit interval using min–max normalization [26]:

$$PR^*_{i,t} = \frac{PR_{i,t} - \min(PR)}{\max(PR) - \min(PR)} \quad (3)$$

This yields a bounded policy-responsiveness component such that: $PR^*_{i,t} \in [0,1]$. This formulation is intentionally based on the stability of observable policy signals over time and evaluates effectiveness without relying on subjective weighting choices.

Dynamics of Investment and Capacity Expansion

Policy responsiveness manifests in deployment through fluctuations in investment flows and capacity growth. Renewable-energy investment and capacity expansion are closely associated with transition dynamics [21, 23]. Accordingly, the study focuses on annual growth changes rather than static values to better capture system dynamics, as the objective is to track system changes over time. For each country i in year t, the growth rates of investment and capacity are computed as:

$$g^{Inv}_{i,t} = \frac{Inv_{i,t} - Inv_{i,t-1}}{Inv_{i,t-1}} \quad g^{Cap}_{i,t} = \frac{Cap_{i,t} - Cap_{i,t-1}}{Cap_{i,t-1}} \quad (4)$$

These indicators ensure that both growths and declines in the activity of solar deployments are caught. Because both positive and negative changes in investment and installed capacity represent changes in deployment dynamics [21, 23], the present study uses the absolute magnitude of annual change as follows:

$$|\, g_{i,t}^{Inv} \,|, |\, g_{i,t}^{Cap} \,| \tag{5}$$

Because investment and capacity changes can be highly skewed, particularly during periods of rapid growth, a logarithmic transformation is applied to reduce scale dispersion [27]:

$$GI_{i,t}^{Inv} = \log(1+|\, g_{i,t}^{Inv} \,|)$$
$$GI_{i,t}^{Cap} = \log(1+|\, g_{i,t}^{Cap} \,|) \tag{6}$$

The two transformed components are then scaled to the unit interval using min–max normalization [26]:

$$GI_{i,t}^{Inv*} = \frac{GI_{i,t}^{Inv} - \min(GI^{Inv})}{\max(GI^{Inv}) - \min(GI^{Inv})}$$
$$GI_{i,t}^{Cap*} = \frac{GI_{i,t}^{Cap} - \min(GI^{Cap})}{\max(GI^{Cap}) - \min(GI^{Cap})} \tag{7}$$

Collectively, these standardized pointers explain the force of financial investment and rate at which capacity is being developed. The specification offers a clear method of contrasting the national settings of various countries since it isolates the growth processes of structures and mere variation of scale.

PIACI – Policies Investment Adoption Coupling Index

Previous studies indicate that renewable-energy transition outcomes depend on interactions among policy support, investment conditions, and deployment processes [21, 23, 24]. Building on these relationships, the present study proposes the Policy–Investment–Adoption Coupling Index (PIACI) as an outcome-based coupling measure. For country $i$in year t, PIACI is defined as:

$$\mathrm{PIACI}_{i,t} = PR_{i,t}^{*} \times GI_{i,t}^{Inv*} \times GI_{i,t}^{Cap*} \tag{8}$$

where:

$PR^{*}_{(i,t)}$ =normalized policy responsiveness

$GI^{Inv*}_{(i,t)}$=normalized investment growth intensity

$GI^{Cap*}_{(i,t)}$=normalized capacity growth intensity

This multiplicative structure reflects the systemic nature of renewable-energy transitions, because weakness in any one component lowers the overall coupling value. For example, strong policy signals combined with weak investment response produce low coupling, just as rapid investment growth without capacity expansion also produces low coupling.

PIACI is inherently limited to the range [0,1], with higher scores representing closer alignment between institutional objectives and realized deployment. Accordingly, it should be viewed as an outcome-driven metric of policy effectiveness, rather than a tool for classifying policy structures in advance.

While policy effectiveness can be observed through deployment dynamics, deployment alone is not sufficient to evaluate efficiency. From a sustainability standpoint, it is important to assess how effectively solar energy systems convert invested financial and infrastructural resources into actual energy output. To capture this dimension, the study develops the CESA indicator.

Previous energy-system studies emphasize the importance of evaluating renewable-energy performance in relation to resource inputs and realized outputs [3, 11, 25]. Based on this input–output efficiency perspective, the present study proposes the raw CESA measure using actual solar generation relative to installed capacity and investment. The raw efficiency measure of country i in year t is:

$$CESA_{i,t}^{raw} = \frac{Prod_{i,t}}{Cap_{i,t} \times Inv_{i,t}} \tag{9}$$

For a given country i in year t, $Prod_{(i,t)}$ is the observed solar power output in MWh in a particular year. The variable $Cap_{(i,t)}$ represents the overall capacity of solar available in MW, and $Inv_{(i,t)}$ is the capital invested in renewable energy systems, which is in USD. Nevertheless, the values are highly dispersed because of huge differences in the levels of investment in different countries and time. Because the raw efficiency values are highly dispersed across countries and years, a logarithmic transformation is applied to improve comparability and reduce scale dispersion [27]:

$$CESA_{i,t}^{log} = \log(1+|\, CESA_{i,t}^{raw} \,|) \tag{10}$$

Normalization techniques such as min–max scaling, decimal scaling, and statistical column normalization have been widely used to improve comparability among variables with different measurement scales and to enhance the performance of analytical model The transformed efficiency values are subsequently normalized to the unit interval using min–max scaling [26]:

$$CESA_{i,t} = \frac{CESA_{i,t}^{log} - \min(CESA^{log})}{\max(CESA^{log}) - \min(CESA^{log})} \tag{11}$$

which yields a bounded efficiency index such that: $CESA_{i,t} \in [0,1]$. To allow cross-country and intertemporal comparability, min-max normalization is done using the combined country-year sample. A larger value of CESA indicates a better transformation of financial and capacity inputs to solar energy output and focuses on efficiency rather than on mere growth. Data dispersion is minimised using a logarithmic transformation, z=log (1+x), and cases where observations are close to zero (causing undefined values) are avoided. So that ratios of capacity or investment can be made without division-by-zero errors, a very small constant is added to the denominator where it is needed. These are non-parametric indicators which are useful to minimize variability and maintain the relative ranking of different country-year observations.

Method for Classifying Coupling and Efficiency States

To study the performance of the system, the classification method is adopted, which measures the alignment and efficiency jointly using PIACI and CESA. The method does not simply squeeze the results into a single index but rather considers coordination and efficiency as two distinct dimensions that can independently develop in times of solar transitions. All observations are placed in a two-dimensional space, which is described by these measures. The space is subdivided into four regions using the median values as the reference points. Patterns of performance and transition behaviour can be identified more effectively with the use of this structure.

Let $\widetilde{PIACI}$and $\widetilde{CESA}$ be the median values of all the country-year data. The pooled-sample medians of PIACI and CESA are used as empirical thresholds to distinguish relatively high and low levels of coupling and efficiency. This median-based classification approach follows previous discussions highlighting the robustness and practical applicability of median split methods when appropriately applied [28]. Each country–year observation is assigned to one of four regimes according to its position relative to these thresholds:

$$\text{Regime}_{i,t} = \begin{cases} \text{HC\_HE}, & PIACI_{i,t} \geq \widetilde{PIACI},\ CESA_{i,t} \geq \widetilde{CESA} \\ \text{HC\_ LE}, & PIACI_{i,t} \geq \widetilde{PIACI},\ CESA_{i,t} < \widetilde{CESA} \\ \text{LC\_HE}, & PIACI_{i,t} < \widetilde{PIACI},\ CESA_{i,t} \geq \widetilde{CESA} \\ \text{LC\_LE}, & PIACI_{i,t} < \widetilde{PIACI},\ CESA_{i,t} < \widetilde{CESA} \end{cases} \quad (12)$$

Abbreviations:

HC_HE = High Coupling_High Efficiency
HC_LE = High Coupling_Low Efficiency
LC_HE = Low Coupling_High Efficiency
LC_LE = Low Coupling_Low Efficiency

This classification produces four analytically distinct transition regimes:

- High Coupling-High Efficiency: This is where there is a good fit between policy direction, financial inputs and deployment processes with high energy output and good implementation. It shows the most desirable transition state.
- High Coupling-Low Efficiency: Here, close coordination of policy and investment fails to lead to efficient results. This can be created because of technological constraints, grid constraints or system operating inefficiencies.
- Low Coupling-High Efficiency: In this case, good performance is realized even in the presence of weak or poor coordination. These consequences can be market based, technologically oriented, or sectoral forces.
- Low Coupling-Low Efficiency Both policy transmission and deployment performance is weak, which implies structurally constrained or inefficient transition pathways.

The median thresholds are distribution sensitive and robust, unlike the conventional classification methods that rely on arbitrary cutoffs. There are three forms of analysis that are complementary to this regime framework:

1. Comparison of leading national transition regimes across countries.
2. Informing appropriate countries about regime changes.
3. Determining policy effort-efficiency mismatches.

The scale does not combine the scale of deployment and sustainability quality. Rather, it isolates the strength of coupling and the efficiency performance, which offers a wider scope on which to interpret policy outcomes. The median thresholds of PIACI and CESA are employed since they are not as sensitive to outliers and can be interpreted in diverse national settings. The regime boundaries are thus obtained through empirically distribution as opposed to arbitrary division. Different thresholds did not affect regime patterns. All the calculations were done in Python through Jupyter Notebook. Data manipulation, normalization, and visualization were performed using standard scientific libraries, which allowed making the workflow reproducible with the help of the dataset and the methodological description.

3. Results and Discussion

The analysis of results and structural and policy implications will be combined in this study to describe the empirical evidence of the proposed paradigm of coupling-efficiency. Results and discussion are presented together to enable assessment of deployment outcomes, efficiency behaviour, and policy relevance within a single analytical framework.

System-Level Coupling–Efficiency Structure — Essentially, there exists an essential asymmetric distribution in the combined distribution of deployment efficiency (CESA) and policy-investment-adoption coupling (PIACI), that can be seen on a global level. The annual observations in the country are largely loosely coupled, and the values of efficiency are spread out. This pattern indicates that, although the institutional and investment environments are comparable, there is a considerable variation in efficiency performance.

As shown in Figure 2, clearly demonstrates a concentration of cases in the lower spectrum of both alignment and efficiency. This indicates that many solar transitions are still marked by weak coordination mechanisms and underdeveloped performance, reflecting gaps in policy effectiveness, investment strength, and implementation capacity.

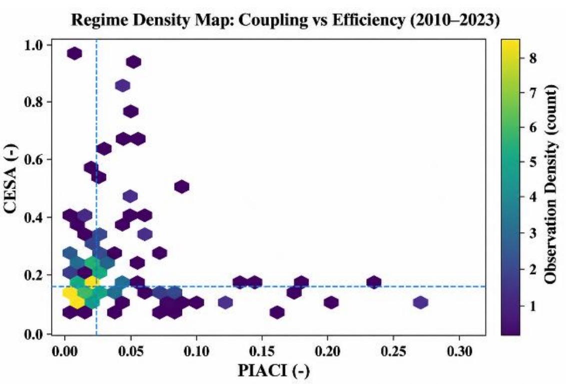

Figure 2. Mapping of country-level yearly observations within the coupling–efficiency space for the period 2010–2023

Observations of high efficiency are not as common and often occur with low to moderate levels of coupling as opposed to high coupling all the time. These findings indicate the possibility of structural decoupling between the scale of expansion and achieved performance and that a higher policy-investment congruence does not necessarily mean a greater deployment efficiency.

Figure 3 shows that deployment efficiency and coupling intensity do not have a linear relationship. The median CESA increases at low coupling strengths and then it levels off before maxing at mid-range coupling strengths, and then severely decreases at higher coupling levels. Response band of the efficiency response increases dramatically with increased coupling, which means that it contains increased uncertainty and dispersion of results.

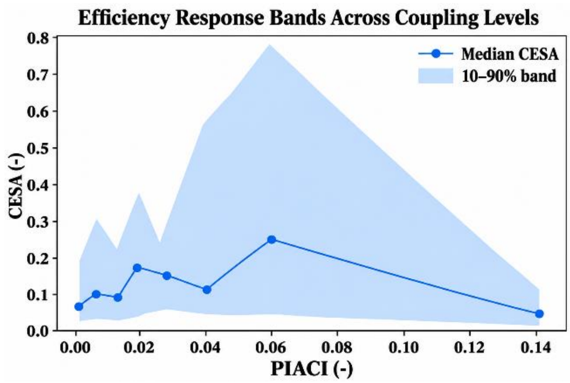

Figure 3. Response distribution of efficiency in response to policy-investment-adoption levels

The declining pattern indicates that pushing policy and investment alignment too far can lead to reduced and even adverse outcomes. High alignment does not ensure steady efficiency gains. Instead, the presence of high efficiency under moderate coupling conditions suggests that balanced system coordination is more beneficial than maximizing alignment. The degree of coupling and the efficiency indexes is shown in Table 2.

Table 2. The degree of coupling and the efficiency indexes

Indicator	Mean	Std. Dev.	Min	Max
Policy component (normalized, 0–1)	0.51	0.14	0.00	1.00
Investment component (normalized, 0–1)	0.30	0.22	0.00	1.00
Capacity component (normalized, 0–1)	0.25	0.20	0.00	1.00
PIACI (dimensionless index, 0–1)	0.04	0.05	0.00	0.29
CESA (normalized efficiency index, 0–1)	0.17	0.19	0.00	1.00

Table 3. Distribution profile of normalized investment and capacity indicators (n = 130)

Indicator	Summary Description
Investment (0–1)	Range: 0.0000 – 1.0000; Mean: 0.2968; Median: 0.2588; Std. Dev.: 0.2157; IQR: 0.1426–0.3838
Capacity (0–1)	Range: 0.0000 – 1.0000; Mean: 0.2514; Median: 0.2047; Std. Dev.: 0.1967; IQR: 0.1325–0.2872

The normalized growth components used in PIACI are shown in Table 3. Both capacity and investment measures are widely dispersed, indicating diversity in deployment momentum within the country-year data. Likewise, the high-performance curve is concentrated in a narrow band of observations, the median values are not much high and the distribution of CESA values is wide (0-1).

Table 4. Distribution characteristics of CESA (normalized efficiency measure)

Metric	Value
Sample size	140
Average level	0.172
Variability	0.194
Lower limit	0.000
Q1 (25%)	0.059
Median (50%)	0.101
Q3 (75%)	0.205
Upper limit	1.000

The distributional characteristics of CESA in the entire sample are shown in Table 4. A small number of countries-year observations are very efficient in that the median is less than the mean, which means that the distribution is skewed to the right. The efficiency of deployment is highly country- and year-dependent with the enormous standard deviation. The dynamics of efficiency is important to look at as well as the behaviour of coupling.

The country-level transition pathways' directional change over time is depicted in Figure 4. Although vertical or diagonal movements show that efficiency rises with a small rise in coupling, horizontal motions show that efficiency rises with a rise in coupling. All these movement patterns demonstrate that, although transition paths of different countries vary, system learning, grid integration, and technological advancement all can influence the increase of efficiency, and not only policy intensity.

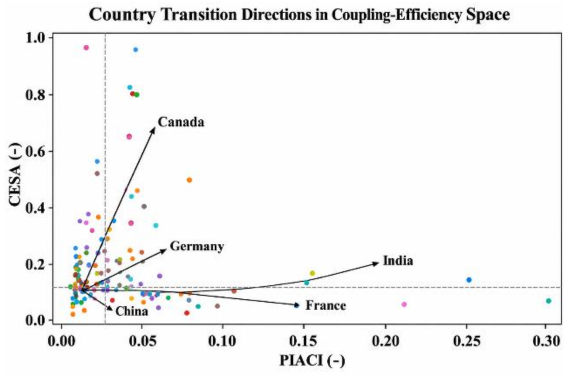

Figure 4. Country-level transition trajectories in coupling–efficiency space (direction and magnitude)

Composition of Cross-Country Regimes and Structural Differences. To study cross-national differences in the results of coupling and efficiency, we divided the observations into four regimes. Table 5 shows that regime composition is very different across countries. There are several high coupling high efficiency years in Germany, India, Japan and the USA, although Canada and the UK have a higher likelihood of low-efficiency regimes which suggests that these countries are characterized by structural constraints. This evidence can be applied to prove that the solar transition pathways are not the same in countries which have similar policy objectives, depending on the national context.

Table 5. Regime occurrence patterns by country

Country	High Coupling–High Efficiency	High Coupling–Low Efficiency	Low Coupling–High Efficiency	Low Coupling–Low Efficiency
Australia	4	2	4	4
Brazil	2	4	5	3
Canada	3	3	1	7
China	2	3	4	5
France	3	3	4	4
Germany	4	5	3	2
India	5	3	3	3
Japan	5	2	3	4
United Kingdom	3	2	3	6
United States	5	2	2	5

Table 6. Country-level dominance of coupling–efficiency regimes

Country	Regime Description	Share (%)
Germany	High coupling – high efficiency	36
India	High coupling – high efficiency	36
United States	Dual dominance (high coupling–high efficiency and low coupling–low efficiency)	36 (each)
United Kingdom	Low coupling – low efficiency	43
Canada	Low coupling – low efficiency	50

The most common regimes and patterns of stability among nations are shown in Table 6. Because the stability of regimes might vary based on institutional coordination, grid integration capacity, and operational efficiency, the results show that performance may not be constant with identical levels of deployment. This variation highlights the importance of shifting evaluation approaches away from total capacity expansion toward indicators that reflect the quality and effectiveness of energy transitions.

Time-Based Transition Patterns and Path Dependence

The regime confluence in space clouds crucial dynamics. Long-term diverging trajectories make up the transition vectors. The observed differences show that some countries follow cyclical or slow improvement patterns, whereas others achieve steady gains in both coordination and efficiency. This highlights the role of path dependence and policy persistence, indicating that solar transitions are not inherently monotonic. Additionally, the graphic shows that there are different levels of regime stability. Whereas other countries are more stable and can withstand longer periods under certain regimes, countries with a high rate of regime changes may have uncertain investment or policy conditions.

Figure 5 reveals that regime membership is highly volatile in most countries. Frequent regime changes are seen even in developed solar economies, suggesting that the advantages of efficiency or coupling are typically not maintained. In many countries, the long-low efficiency regime trend is especially significant as it implies dependency on routes and the possibility of very established deployment systems.

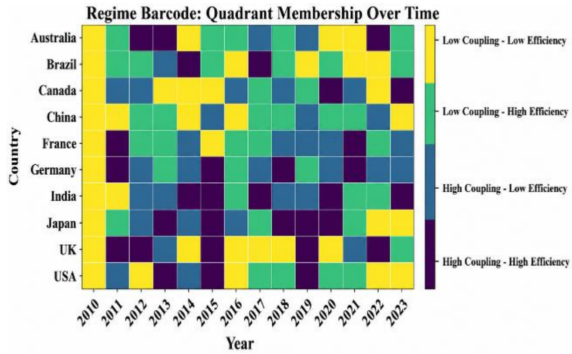

Figure 5. Country-level evolution of coupling–efficiency regimes over time (2010–2023)

These trends indicate that cross-sectional and static benchmark cannot be utilized to determine the solar transition performance. The overall regime shifts on a year-to-year basis of these processes are summarized in Table 7. The durability of low-efficiency regimes highlights inherent system rigidities, which hinder rapid movement away from suboptimal deployment patterns.

It is not generally possible to produce long-term changes with short-term acceleration in policy alone without the long-term investment and flexibility of the system. It has been observed that the high coupling, and high efficiency regimes transitions are very stable and the low coupling, and low efficiency regimes transitions are also very stable. This indicates that long-term efficiency effect does not always occur with policy-investment alignment. The fact that the transitions between the states of increased and decreased efficiency are rather frequent, also speaks of the fact that it is not an easy task to maintain the performance on a long-run basis. Overall, this asymmetry in the transition suggests that weaker regimes are more persistent, meaning that there is structural doubt in maintaining high-performing solar transition pathways.

Table 7. Movement patterns across coupling–efficiency regimes

Initial Regime	Transition Outcomes
HC_HE	Remains: 7; shifts to HC_LE: 13; to LC_HE: 10; to LC_LE: 4
HC_LE	Moves to HC_HE: 8; remains: 3; shifts to LC_HE: 7; to LC_LE: 10
LC_HE	Moves to HC_HE: 9; to HC_LE: 9; remains: 6; to LC_LE: 5
LC_LE	Moves to HC_HE: 8; to HC_LE: 2; to LC_HE: 7; remains: 12

High-Performance Cases and Structural Imbalances:

Insights for policy design can be gained by examining both well-performing transitions and instances where high alignment among policy initiatives and financial investment does not result in improved efficiency.

The findings presented in Figure 6(a) indicate that the overall financial growth is generally higher than the increase in operational efficiency, and investment and policy indicators often prevail in most of them. Yet, more efficient observations demonstrate more equal policy, investment, and capacity input, which implies the enhanced deployment results owing to the increased level of system coordination.

Figure 6(b) condenses the regional patterns of the transition risk among countries, where the bigger the markers the longer lasting the mismatch between coupling and efficiency, and the high regime volatility.

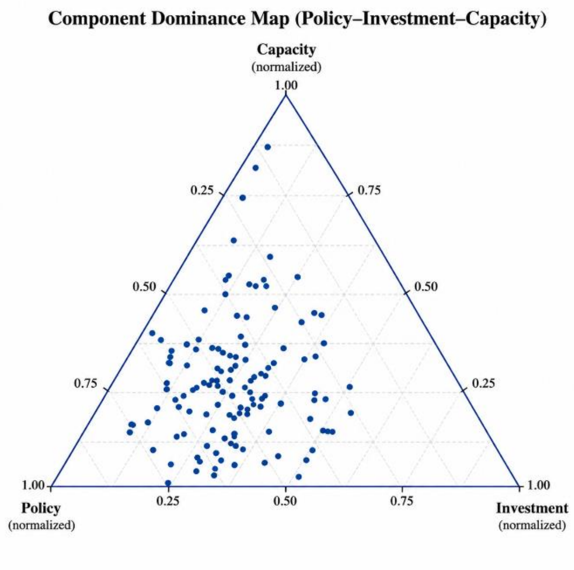

Figure 6(a). Distribution of impacts across policy, investment, and capacity components

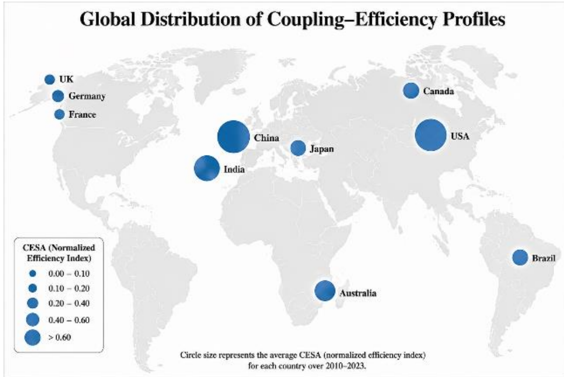

Figure 6(b). Worldwide depiction of risk exposure arising from differences in alignment and transition processes

Table 8 presents representative high coupling–high efficiency cases, demonstrating that strong performance is achievable under moderate and well-balanced coupling conditions.

The findings indicate that advanced markets, characterized as having structural conflicts of policy ambition, scale of investment and system integration capacity are equally vulnerable to transition risk as emerging markets. These results indicate that transition performance should be measured based on both scale and stability-based measures.

Table 8. Benchmark cases representing effective coordination and high-performance levels

Country	Year	PIACI (scaled)	CESA (scaled)
Australia	2013	0.248	0.119
India	2023	0.191	0.104
UK	2012	0.156	0.118
Japan	2019	0.148	0.101
Germany	2016	0.086	0.478
Japan	2017	0.065	0.220
Japan	2011	0.061	0.344
USA	2018	0.059	0.282
Germany	2011	0.055	0.760
USA	2021	0.054	0.193

Table 9. Illustrative cases highlighting variations in coupling–efficiency states across countries and years

Country	Year	PIACI (%)	CESA (%)	Regime Type
Australia	2013	24.8	11.9	HC_HE
India	2023	19.1	10.4	HC_HE
United Kingdom	2012	15.6	11.8	HC_HE
Japan	2019	14.8	10.1	HC_HE
Germany	2016	8.6	47.8	HC_HE
Canada	2021	28.6	2.5	HC_LE
United States	2014	27.6	5.0	HC_LE
India	2018	21.3	2.8	HC_LE
France	2014	16.6	0.0	HC_LE
China	2013	2.0	19.3	LC_HE
Germany	2021	1.8	27.2	LC_HE
United Kingdom	2013	1.8	6.9	LC_LE
China	2022	1.4	4.7	LC_LE

Table 9 also demonstrates that high efficiency is not a necessary consequence of high coupling, some of the low-coupling observations also yield high efficiency. This implies that effective solar shifts need to be based on the equilibrating conditions of the system, instead of extreme expansion policies. Table 10 summarizes the average coupling of efficiency differences between countries. We may say that it has negative returns until we can better integrate grid operation and performance since the positive gaps indicate growth that is greater than improvement of efficiency. Conversely, close to zero or negative gaps represent balanced transition pathways or efficiency-driven transition pathways. Overall, best-practice outcomes are typically linked to moderate and well-integrated deployment environments in most cases, as opposed to fast and aggressive growth patterns. Focusing solely on increasing capacity without enhancing efficiency can limit long-term gains. As a result, supportive actions are required to tackle issues in system performance, grid compatibility, and operational optimization.

Table 10. Comparative profile of coupling–efficiency gap across countries

Country	Gap Trend	Explanation
Germany	Negative	Transition driven primarily by efficiency improvements
India	Near neutral	Balanced progression between expansion and efficiency
United States	Positive	Growth in expansion outpacing efficiency gains
United Kingdom	Positive	Ongoing inefficiencies despite expansion efforts
Canada	Positive	Structural mismatch affecting transition performance

Uncertainty, Transition Dynamics, and System Stability:

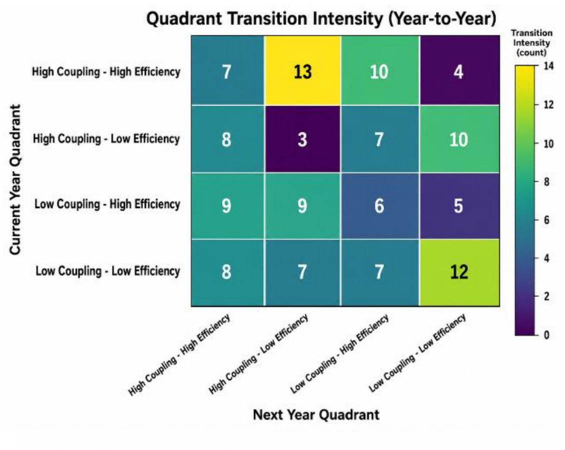

Figure 7. Variation in yearly transitions between different coordination and performance conditions

The last robustness test is the determination of the observed patterns, and these could be stable or volatility-driven. The CESA response bands of quantile responses have a non-linear correlation with PIACI variations. Sustained gains in efficiency appear primarily at elevated coupling levels, although instability persists at the extremes of both weak and strong coupling

Table 11. National variations in system coupling and fluctuation levels

Country	Mean	Volatility	Risk Interpretation
Germany	Moderate	Low	Stable performer
India	Moderate	Moderate	Transitional
USA	Moderate	High	Volatile
UK	Low	Moderate	Structurally weak
Canada	Low	High	High-risk

Figure 7 presents the annual transition frequencies, which help assess the stability of coupling–efficiency regimes. A high rate of transitions away from high-efficiency regimes indicates structural instability, while continued persistence within low-efficiency regimes reflects underlying systemic weaknesses. Specifically, the frequent switching between high-alignment, high-efficiency configurations and low-efficiency outcomes reflects differences in overall performance are frequently transient and challenging to maintain over time.

When combined with low volatility, countries exhibit more predictable transition outcomes, whereas policy signals become less effective under conditions of high volatility. Table 11 illustrates how these findings support the adoption of resilient and effective solar energy transitions through sustained policy continuity.

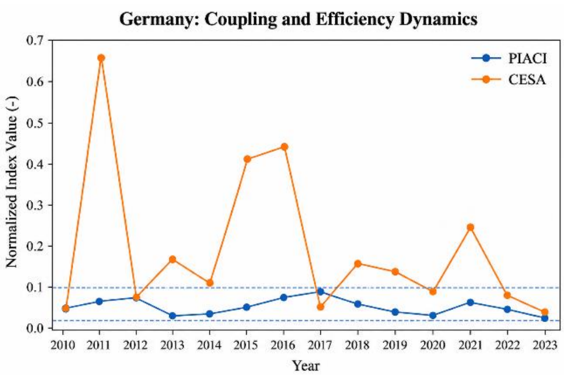

Figure 8(a). Germany: progression of system coordination and efficiency performance from 2010 to 2023

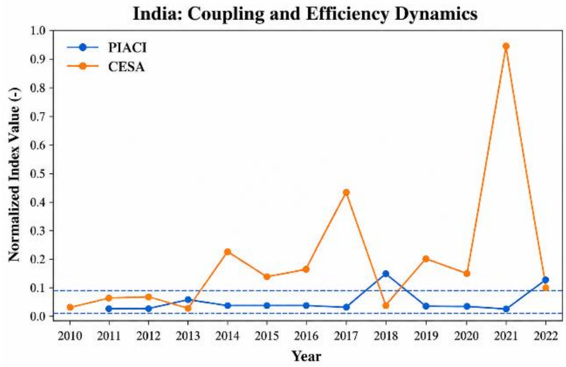

Figure 8(b). India: progression of system coordination and efficiency performance from 2010 to 2023

Counter-national tendencies are shown in Figures 8(a) and 8(b). India is highly efficient with very low and significantly divergent coupling which means that there are bursts of high efficiency which are due to situational or project-based causes rather than policy. Meanwhile, Germany exhibits relatively stable coupling alongside occasional surges in efficiency, reflecting the characteristics of a mature system where achieving incremental gains becomes increasingly challenging. These observations reinforce the broader finding that the strength of coupling alone is not a reliable predictor of efficiency outcomes.

Implications for Policy Design

Implication 1: The extent of deployment in itself is not enough to ascertain effectiveness of the transition. What the conclusion of this paper implies is that it is typical to have a combination of high levels of investment and high installed capacity but low deployment efficiency. This absence of empirical association between PIACI and CESA indicates that the success measures that are scale-based are highly skewed in measuring transition success. The weak empirical correspondence between PIACI and CESA indicates that scale-based measures alone may provide an incomplete assessment of transition success. Capacity-based monitoring systems may therefore fail to distinguish between expansion that improves system performance and expansion that occurs without corresponding efficiency gains, potentially leading to misleading assessments of policy effectiveness.

Implication 2: One structural risk relating to solar transitions is policy volatility.

The regime-switching and volatility analyses indicate that high but unstable policy–investment coupling is associated with a greater tendency to revert to low-efficiency regimes. It implies that irrespective of the objectives of the policy, the short-term incentives policy systems or more frequent system redesigns lead to system instability. In the long run, volatility eventually puts a boundary on efficiency gains and transition consolidation.

Implication 3: Policy intensity is less important than coordination.

This study finds that relatively small, consistent coupling (as opposed to aggressive growth policies) is the key to high efficiency in best-practice situations. In this sense, during solar transitions, which are coordinated social-technical systems, all policy signals, investment reactions, and deployment dynamics should alter together. Thus, policy effectiveness depends more on system coherence than on the intensity of individual policy instruments.

Implication 4: Inefficiency cautions against structural impediments, but not a deficiency in policies.

The research results suggest that deployment congruency would be significantly quicker than efficiency performance in case there are continued positive couplings and efficiency gaps. It suggests that instead of no policy effort, the lack of measurement is often due to downstream constraints such as grid integration, technology utilization, or siting restrictions. Nevertheless, it would be wrong to merely consider low efficiency as a policy failure in order to identify the problem of the shortcomings of the transition.

Implication 5: Outcome-based frameworks make a priori learning of policy possible.

The results of this study indicate that the PIACI–CESA framework has weak and unequal transition paths, which may eventually result in the establishment of inefficiencies because deployment alignment and efficiency outcomes are decoupled. It suggests that in the case of long-term decarbonization strategies, the logic of policy learning will be changed as the adjustment to the changing situation becomes reactive instead of the evident failure to anticipate the emerging threats.

Table 12 brings together the key trends identified in the analysis, highlighting relationships between system coordination, efficiency levels, volatility, and regime dynamics. Rather than offering direct recommendations, the table serves as a conceptual bridge, linking observed empirical patterns with broader policy interpretations. It captures how different transition pathways unfold in practice and how these variations can be understood in a policy context.

In conclusion, the proposed framework supports more adaptive and forward-looking policy design by clearly distinguishing between alignment in deployment and actual efficiency outcomes.

Table 12. Empirical patterns and their policy interpretation in solar transition analysis

Analytical Aspect	Key Observation	Policy Insight
Deployment scale vs. performance	Large capacity expansion and high investment levels are often accompanied by relatively low efficiency outcomes	Reliance on scale-based metrics alone can misrepresent actual transition effectiveness
Coupling strength	Higher PIACI levels do not consistently correspond to improved efficiency performance	Alignment between policy and investment does not necessarily ensure effective system outcomes
Policy consistency	Fluctuations in PIACI are linked with frequent shifts between regimes	Policy instability introduces structural uncertainty in transition processes
High-performing cases	Optimal efficiency tends to occur under moderate and stable coupling conditions	Balanced system coordination is more effective than aggressive expansion strategies
Coupling–efficiency divergence	Positive gaps between PIACI and CESA persist across multiple country cases	Efficiency limitations are often driven by downstream structural and operational factors
Regime continuity	Low-efficiency states tend to persist over time	Early-stage inefficiencies may become embedded in long-term transition pathways
Variation in outcomes	Significant differences exist across countries and time periods	Standardized policy benchmarks fail to capture context-specific dynamics

This distinction enables policymakers to move beyond reactive adjustments and toward more strategic management of energy transitions, ensuring that solar expansion is not only rapid but also efficient, stable, and sustainable over time.

4. Conclusions

This study integrates policy–investment–adoption coupling with deployment efficiency to develop an outcome-based analytical framework for evaluating solar energy transitions. The cross-country panel analysis for 2010–2023 reveals persistent differences between deployment alignment and efficiency performance, as well as substantial heterogeneity in national transition pathways and regime-switching behaviour. The findings demonstrate the limitations of scale-based assessment approaches by showing that strong policy alignment and investment growth do not necessarily translate into efficient outcomes. By incorporating coupling behaviour, deployment efficiency, and temporal dynamics, the proposed framework provides a broader assessment of renewable-energy transition performance than conventional capacity-based indicators. Overall, the results indicate that sustainable solar transitions depend on coordinated system functioning, policy stability, and operational efficiency rather than on the magnitude of expansion alone.

5. Limitations and Future Work

Despite its contributions, the study has several methodological limitations. To start with, it does not consider local operating limits, like grid integration issues within a region since it is examined using aggregate country level indicators. Second, PIACI is not used to distinguish between various types of detailed policy instruments but rather is used to evaluate continuity patterns of policies. Third, technology specific considerations such as storage integration or curtailment effects are not explicitly captured in the CESA, which is founded on real energy generation of investment and capacity.

Future studies could incorporate additional grid-level and technology-specific variables, together with higher-resolution subnational data, to improve the precision of the diagnostic assessment. The proposed approach could also be extended to hybrid renewable-energy and storage-integrated systems to evaluate emerging transition pathways.

Acknowledgements

The authors acknowledge the academic support and research environment provided by their respective institution during the preparation of this manuscript.

Nomenclature

Symbols	Description
(i, t)	Country–year observation
$CESA$	Median Carbon Efficiency of Solar Adoption over pooled observations (dimensionless)
$CESA_{i,t}$	Carbon efficiency of solar adoption for country *i* at time *t*
$CESA_{i,t}^{raw}$	Scaled (normalized) carbon efficiency measure
$D_{i,}$ ▯	Dummy variable indicating presence of solar policy
$E_{i,}$ ▯	Realized solar electricity production in country *i* during year t
$g_{i,t}^{Cap}$	Annual growth rate of installed solar capacity
$g_{i,t}^{Inv}$	Annual growth rate of renewable investment
i	Country index
$\tilde{I}_{i,}$ ▯	Normalized investment growth intensity
$J_{i,}$ ▯	Employment generated by solar energy activities
$K_{i,}$ ▯	Installed solar capacity in country i during year t (MW)
$\tilde{K}_{i,}$ ▯	Normalized capacity growth intensity
$P_{i,}$ ▯	Raw policy responsiveness measure (dimensionless)
$PR_{i,t}^{*}$	Normalized policy responsiveness component
$R_{i,}$▯	Renewable energy share in total energy consumption (%)
$Regime_{i,}$ ▯	Coupling–efficiency regime classification
t	Year index

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