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Evaluating solar photovoltaic power efficiency based on economic dimensions for 26 countries using a three-stage data envelopment analysis

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HIGHLIGHTS

- A three-stage data envelopment analysis model assessed solar PV power efficiency.
- Solar PV power efficiency was measured for 26 countries from 2000 to 2020.
- The measurement of solar PV power efficiency was based on economic dimensions.
- Most of the countries with high average solar PV power efficiency are high-income.
- The external environment underestimates the average solar PV power efficiency.

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ABSTRACT

This paper proposes a new concept for solar photovoltaic (PV) power efficiency and explores a new direction by considering such efficiency at the national level and from a macro perspective. Solar PV power efficiency is defined in this study as a measure of investment in, and management and development of, solar PV generation in each country, along with the efforts made to increase such investment and implement development measures. Solar PV power efficiency is considered instrumental in addressing climate change and achieving sustainable development. Therefore, its assessment is of interest to the vast majority of economies. This study used economic dimensions to analyze solar PV power efficiency and its influencing factors in 26 countries from 2000 to 2020 in a three-stage data envelopment analysis. The results show that, first, the overall solar PV power efficiency of the 26 countries is 0.762, which leaves significant room for improvement, and that most of the countries with high average solar PV power efficiency are high-income. Second, increasing GDP per capita and lowering carbon dioxide emissions contribute to higher solar PV power efficiency. The proportion of the urban population in the total population also impacts solar PV power efficiency. Third, the extent to which external environmental variables affect solar PV power efficiency varies across countries. The 26 countries considered generally had higher average solar PV power efficiency in the third stage than in the first stage, indicating that external environmental variables can lead to an underestimation of solar PV power efficiency. The range of difference varies by country; Mexico, Morocco, Australia, Japan, and South Korea saw the most significant increases in solar PV power efficiency, all exceeding 0.3. In addition, this study makes several measures to improve solar PV power efficiency. Overall, the findings contribute to understanding the trends and influencing factors of solar PV power efficiency in 26 countries and can provide a new calculation method for studying solar PV power efficiency.

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1. Introduction

1.1. Background

Renewable energy achieved a 28.8% share of the global electricity supply in 2020, the highest level on record, with solar photovoltaic (PV) and wind each accounting for about one third of the total renewable electricity generation growth that year [1]. Solar PV generation uses semiconductor materials to convert sunlight into electricity [2,3]. Specifically, a solar PV generation system consists of solar cells, batteries, inverters, chargers, discharge controllers, solar tracking control equipment, and other systems [4]. Due to its pollution-free, environmentally protective nature, solar PV generation is one of the most developed energy conversion methods [5]. Meanwhile, declining fossil fuel savings and rising greenhouse gas emissions have intensified research activity in the field of solar PV generation. Worldwide solar PV generation reached 680,952 GWh in 2019 [6], indicating that the sector is relatively well-developed in countries such as the United States, China, India, and member states of the European Union. However, there are relatively few studies on how to effectively evaluate solar PV power efficiency in these countries. Solar PV power efficiency is given a different definition in this paper from that used in power generation systems, meaning that it cannot be defined as the ratio of output power to input power. In this study, solar PV power efficiency is defined as a measure of each country's investment in, and management and development of, solar PV generation (see Section 2.1 for the detail).

Due to the importance of the impact of solar PV generation in addressing climate change and achieving sustainable development, the vast majority of economies recognize the significance of assessing solar PV power efficiency. In particular, assessing solar PV generation has strong practical implications for accelerating the energy transition and reducing carbon emissions, providing stakeholders and policymakers with more scientific evaluation criteria. For example, investment in the global renewable energy sector has grown from less than $50 billion per year in 2004 to approximately $300 billion per year recently, with solar PV generation attracting 46% of global renewable energy investment between 2013 and 2018 [7].

By the end of 2020, the global installed solar PV capacity reached 710,700 MW, with 38.7% of the new installed capacity in 2020 coming from China and 12.3% from North America; the European Union accounted for 16.8% of the world's solar PV generation that year [8]. The Japanese government has been paying more attention than other countries to developing the solar PV residential market, installing solar PV generation systems in public buildings and issuing energy-saving product consumption points and green power certificates to the public [9]. India has announced a new 2030 target of 500GW of total installed renewable energy capacity by 2070; the United Kingdom government has launched the contracts for difference support scheme for low-carbon technologies, which aims to secure 12 GW of capacity open to more renewable energy technologies [10]. In 2016, most countries signed the Paris Agreement to jointly curb the global warming trend. In order to achieve that goal, an energy transition is necessary from fossil to zero-carbon energy sources, such as solar PV generation, and energy-related carbon dioxide emissions must be reduced to mitigate climate change and achieve sustainable development. Almost all countries that signed the Paris Agreement are actively implementing their energy transition.

1.2. Literature review

Most previous studies have focused on the technical aspects of PV and the analysis of PV performance by firms which have benefited from PV technology advances and market promotion. The performance assessment models can be classified into three categories: enterprise, power plant, and technology. The enterprise model assesses the business performance of PV companies, the power plant model assesses the operational performance of PV plants, and the technology model assesses power after multiple life cycles of different PV technologies. Table 1 lists the advantages and disadvantages of each performance assessment model.

The enterprise model is used to develop a systematic model to evaluate the performance of PV companies or projects. However, as it is usually applied to evaluate the performance of individual PV companies or PV projects without considering the whole PV industry, it is neither comprehensive nor reasonable. Lee et al. [11] proposed a performance assessment model that evaluates the current business performance of Taiwanese crystalline silicon PV firms by integrating hierarchical analysis and data envelopment analysis (DEA). The importance of expert opinions is obtained through hierarchical analysis, after which DEA is used to select which firms are efficient. Wang et al. [12] used DEA and gray correlation analysis to assess the contribution of PV poverty alleviation project efficiency to targeted poverty alleviation in China. They found that China's investment in PV poverty alleviation projects is effective but that its impact on poverty alleviation is overestimated.

Chang et al. [13] used DEA to assess the operational efficiency of each company by combining four years of financial data from the top 10 global PV companies. The authors found that 17.5% of PV companies reach the ideal efficiency. Lee et al. [14] first applied fuzzy hierarchical analysis and DEA to evaluate the business performance of PV companies, followed by the Malmquist productivity index to assess the efficiency of each company over time, and proposed a framework for evaluating the performance of companies in the PV industry. Wu et al. [15] used an improved three-stage DEA model to assess the performance efficiency of PV poverty alleviation projects and found that such efficiency in China is low due to an unreasonable production scale. PV companies and PV projects only provide individual and not overall performance and therefore do not apply to the analysis of the potential of the PV industry as a whole.

The power plant model uses environmental conditions or geographic location factors to obtain a suitable site for a PV plant and identify factors that may affect its operational performance. The power plant model also entails calculating the best location for a PV plant in non-built-up areas and identifies the most significant factors affecting the operational efficiency of a PV plant in built-up areas. Sozen et al. [16] used DEA to determine the location of PV plants in 30 different cities in Turkey and assessed the efficiency scores for one year using a modified ideal solution similarity method. Wang et al. [17] integrated the DEA, gray hierarchical analysis, and sequential preference of the gray technology method to assess suitable areas and locations for PV installation in Vietnam using qualitative and quantitative valid criteria. The results were then used to identify sites for PV plants throughout Vietnam, saving on costs and resources, and the authors also recommended that

Table 1
The advantages and disadvantages of each performance assessment model.

Model	Advantages	Disadvantages
Enterprise model	• Suitable for assessing the corporate performance of a division in the PV supply chain	• Cannot analyze the whole PV industry • Incomplete evaluation
Power plant model	• Assesses integrated efficiency • Improves the investment environment • Considers site selection issues • Clarifies the impact of environmental factors	• The existence of constraints such as infrastructure, worker skills, local government regulation
Technology model	• Evaluates the power generation performance of different PV modules	• Not applicable to the estimation of the power generation potential of large-scale PV systems

the government established applicability policies. Wang et al. [18] used a three-stage analysis of the average operating efficiency of 70 PV plants in the United States to verify the impact of environmental factors and statistical noise on the operating performance of PV plants. Furthermore, their analysis clarified the need to consider environmental factors in the performance evaluation of PV plants.

Mostafaeipour et al. [19] used a hybrid approach consisting of DEA, balanced scorecards, and game theory to assess the techno-economic feasibility of building a PV plant in Iran. Their proposed hybrid approach was superior to a simple DEA, resulting in relatively accurate results. Khanjarpanah et al. [20] proposed a new algorithm for the DEA of a dual preamble network to develop a hybrid power plant of wind and PV, then considered economic, social, environmental, and other factors and, finally, gave a priority ranking to establish the candidate location of the hybrid power plant. Despite the high accuracy of analyses for the siting of PV plants and assessment of their operational performance, the estimated plant model is only applicable to urban areas and requires the support of government departments due to conditions such as the need for local infrastructure and worker skills.

With the growth of PV technology models and the development of the PV market, it has become increasingly important to assess the energy efficiency of PV technologies. Furthermore, experiments can test the technical efficiency scores of different PV modules. Therefore, PV technology is widely promoted for use in PV cell manufacturing. However, the economic potential of applying PV technology to PV cell manufacturing is rarely analyzed. Haeri [21] used the DEA to evaluate and compare the mean size of PV technology performance under four states: total factor, technology factor, economic factor, and payback period factor. The mean efficiency score of thin-film PV technology was higher than the mean efficiency score of crystalline silicon PV technology only in the case of the payback period factor. Ratner and Lychev [22] used DEA to estimate multiple lifecycle environmental impacts of different PV technologies. Their results showed that current thin-film technologies meet the need for fewer resources and energy in manufacturing activities. Ghosh et al. [23] combined Shannon entropy and DEA to evaluate the relative performance of different PV arrays under different environmental conditions. Their results help policymakers and researchers use environmental factors to improve the performance ratio of PV projects. Yang et al. [24] used an integrated fuzzy hierarchical analysis and a DEA model to evaluate solar PV power efficiency and examined nine potential influencing factors using Tobit regression. Although it is possible to evaluate the magnitude of PV performance in different environments using technical models, the aim of practical applications is not to improve PV module power generation efficiency in isolation but to evaluate solar PV power efficiency as a whole.

Based on the literature review, current studies on the use of DEA for PV assessment have the following limitations:

(1) There are few studies on solar PV power efficiency at the national level. Although solar PV generation is widespread and can provide electricity to meet the energy needs of economic development, few analyses have been conducted to assess solar PV power efficiency.

(2) Most studies on PV efficiency have focused on micro-analysis, for example of the enterprise, power plant, or technology model. However, macro-analysis from an economic perspective has been neglected. Therefore, it is necessary to assess solar PV power efficiency from an economic perspective at the macro level.

(3) A traditional DEA only compares evaluated objects in environments with the same characteristics. As Norton et al. [25] pointed out, many decision-making units (DMUs) operate under site characteristics that are significantly different from those experienced by other DMUs, which may affect their efficiency ratings. It would be unfair to focus only on efficiency ratings and ignore environmental differentiating factors among DMUs. To address the impact of differentiation, researchers have summarized in detail how environmental impacts can be removed from DEA so that efficiencies can be reasonably assessed [26–30]. The three-stage DEA is the most prevalent approach [31–33].

1.3. Motivations and contributions

To address the research gap identified in the previous section, the main objective of this study is to assess solar PV power efficiency at the national level using a three-stage DEA approach based on economic dimensions to ensure and guide the sustainable development of the PV industry. This paper evaluates solar PV power efficiency from an economic perspective in 26 countries from 2000 to 2020. 26 countries (i.e., Canada, Mexico, the United States, Austria, Belgium, Czech Republic, Denmark, France, Germany, Greece, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland, the United Kingdom, Israel, Egypt, Morocco, Australia, China, India, Japan, Philippines, and South Korea) were selected for consideration in this study due to data availability. Moreover, these 26 countries are located in Asia, Europe, the Americas, Africa, and Oceania, spanning the northern and southern hemispheres, and have different natural and socioeconomic characteristics.

The economic dimensions considered in this paper refer to government provision of substantial support and subsidies for solar PV generation, which generally include solar PV generation planning policies, science and technology, research and development activities, capital costs, power costs, and market resource allocation. Economic development, population growth, and climate change have put considerable pressure on power supplies, leading to power supply instability in recent years. To reduce this instability, environments must be created that enable the development of solar PV generation by improving technological innovation, reducing related costs, enacting supportive policies and regulations, and developing independent grids and microgrids. Hence, it is necessary to assess solar PV power efficiency from an economic perspective in the 26 selected countries. This study used a three-stage DEA model to assess the changes in solar PV power efficiency in these countries by considering socioeconomic, technological innovation, and external environmental variables. In particular, gross capital formation (% of GDP), labor, solar PV installed capacity, the cumulative number of solar PV patents, solar PV generation, the proportion of the urban population in the total population, GDP per capita, and carbon dioxide emissions were the variables used in the evaluation.

In the first stage of the analysis, DEA was applied only to inputs and outputs to obtain preliminary results for solar PV power efficiency. In the second stage, stochastic frontier analysis (SFA) was applied to further analyze the effects of external environmental variables on efficiency, thus enabling better assessment, in the third stage, of the changes in solar PV power efficiency in these countries. Finally, the results obtained in the third stage excluded the effects of the external environment and statistical noise. This study makes the following contributions:

(1) It attempted to assess solar PV power efficiency in 26 countries using a three-stage DEA model. DEA was applied to inputs and outputs in the first stage to obtain a preliminary assessment of solar PV power efficiency, since the first stage did not consider the effects of external environmental variables and statistical noise on solar PV power efficiency. As such, the second stage used stochastic frontier analysis to attribute the changes in solar PV power efficiency in the first stage to external environmental variables, management inefficiencies, and statistical noise. In the third stage, the adjusted input data was applied to the DEA to repeat the first-stage analysis. The third stage of the reassessment of solar PV power efficiency provided a more accurate assessment than traditional analysis, as the effects of external environmental variables and statistical noise had largely been eliminated in the second stage. In particular, this study provides a measure and analysis of trends in solar PV power efficiency over time, providing policymakers with a solar PV power efficiency indicator to use as a benchmark that they can refer to and understand.

(2) It uses panel data from 2000 to 2020, which contains a broader range of observation content than most previous DEA studies that have

used panel data. Solar PV power efficiency is considered instrumental in addressing climate change and achieving sustainable development. The importance of assessing solar PV power efficiency is of interest to the vast majority of economies. A country should measure solar PV power efficiency and keep related records. Therefore, this study used economic dimensions in its analysis.

The remainder of the paper is organized as follows. Section 2 covers the methodology and data, and Section 3 presents and discusses the estimation findings. Finally, Section 4 discusses potential policy implications and future research prospects.

2. Methodology and data

2.1. Overall summary of the three-stage DEA model

Solar PV power efficiency in this study is defined as a measure of investment in, and management and development of, solar PV generation in each country, as well as efforts made to increase such investment and implement development measures. It is calculated as the ratio of each country, in different periods, of the output of solar PV generation to the input of gross capital formation, labor, solar PV installed capacity, and the cumulative number of solar PV patents. The traditional DEA models used to analyze efficiency scores tend to ignore slack variables and thus produce biased evaluation results for radial and angular reasons [34]. The three-stage DEA model avoids this bias better than the traditional DEA model and eliminates the influence of external environmental variables and statistical noise on the results. Therefore, we used the three-stage DEA model developed by Fried et al. [35]. The constructions of the model were divided into three parts (Fig. 1). We used a traditional DEA model (Banker, Charnes, and Cooper (BCC) model based on the input perspective; that is, a linear equation of variable returns to scale based on input orientation) to obtain the initial efficiency scores in the first stage. In the second stage, we considered the three categories that affect the efficiency score (external environmental variables, statistical noise, and management inefficiencies)—that is, the effects of these three categories on the slack variables—separating the effects of external environmental variables and statistical noise through the SFA model to obtain the adjusted inputs. In the third stage, we repeated the first-stage analysis to obtain new efficiency values, which, unlike the first-stage efficiency values, removed the effects of the external environment and statistical noise.

2.2. First stage: The initial DEA solar PV power efficiency evaluation

The initial solar PV power efficiency evaluation was performed using conventional DEA, where efficiency was assessed as the ratio of the total output of the DMU to the total input, accomplished by aggregating an endogenous weighting scheme for the input and output data. Either orientation was allowed, and we decided to use an arbitrary input orientation for uniformity.

Banker et al. [34] developed the variable returns-to-scale envelopment from a linear programming:

$$\begin{aligned}
&\min_{\theta,\ \lambda}\ \theta\\
&subject\ to\ \ \theta x_{\circ} - X\lambda \geq 0\\
&Y\lambda \geq y_{\circ}\\
&e\lambda = 1\\
&\lambda \geq 0,
\end{aligned} \tag{1}$$

where $x \geq 0, x \neq 0$ are a DMU's $M \times 1$ vector of inputs, $X = \left[x_{1,\dots,}x_J\right]$ is an $M \times J$ matrix of input vectors in the comparison set, $y \geq 0, y \neq 0$ are a DMU's $S \times 1$ vector of outputs, $Y = \left[y_{1,\dots,}y_J\right]$ is an $S \times J$ matrix of output vectors in the comparison set, λ is a column vector whose elements are all non-negative, and e is row vectors with all elements equal to 1. There are J DMUs in the comparison set; this imposes a convexity condition on allowable ways in which the comparison is set for each DMU; the data of the DMU being evaluated are subscript "∘", and the DMUs are solved J times.

The optimal solutions to the envelopment form the linear programming (1) provide an initial solar PV power efficiency value θ evaluation for each DMU. The optimal solutions are represented by $(\theta,\ \lambda,\ s^-,\ s^+)$, where s^- and s^+ represent the input excesses and output shortfalls, respectively. If $\theta = 1$, that is, no slack (i.e., $s^- = 0,\ s^+ = 0$), then we call it efficient; otherwise, it is inefficient.

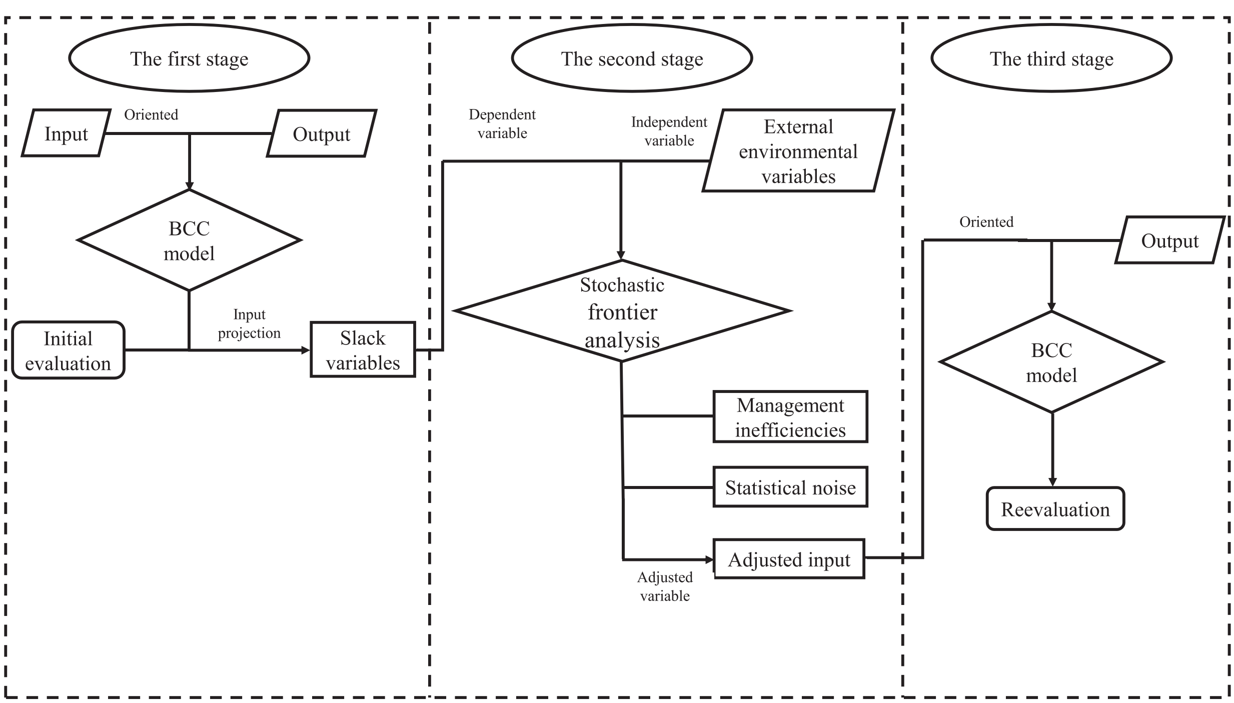

Fig. 1. A framework of a three-stage data envelopment analysis model.

Our choice of DEA to assess efficiency was influenced by three different factors: the efficiency with which management organizes, the characteristics of the external environment in which operations are conducted, and some non-human uncontrollable random effects [28,36]. The first factor is internal, and the second and third are external. To separate the effects of these factors on the results, the model must be stochastic; however, the DEA model used in the first stage is deterministic, which means that this cannot be done within the framework of Section 2.2; hence, the processes described in Section 2.3 were carried out.

2.3. The second stage: Decomposing the first-stage slacks by using SFA

We determined the presence of inefficiency in the first stage by looking at two types of slack: input overload and output underload. However, two other factors, namely external environmental variables and statistical noise, also have an impact on slack. To decompose the slack in the first stage into these three factors, we used SFA. In the second stage, we distinguished the effects of managerial inefficiency and statistical noise by regressing the observable external environmental variables and the mixed error term, which allowed the independent variable (external environmental variables), the unilateral error component (managerial inefficiency), and the symmetric error component (statistical noise) to influence the slack due to the SFA's advantage of asymmetric error terms [35].

We used SFA regression for separation; however, there are multiple approaches regarding the selection of the dependent variable, and we referred to Fried et al. [35] for an explanation of the selection of the dependent variable, as shown in Fig. 2. Regarding the kinds of dependent variables, we could either interpret all input excesses s^- and output deficiencies (output shortfalls) s^+ as dependent variables or only s^- as dependent variables. Both approaches are feasible, but considering that we were calculating the results from the input perspective in stage 1, we preferred to interpret only s^- as the kinds of dependent variables compared to the output perspective. Regarding the number of dependent variables, we could either evaluate each input excess as the dependent variable in each individual SFA regression or stack all of them as the dependent variable in a single SFA regression. The former method has the advantage of capturing the different effects that all of the independent variables (external environmental variables) have on each dependent variable (input excess); the latter has the advantage of creating a greater degree of freedom and broader estimation statistics. Again, both methods are feasible, but, on balance, it was decided that the advantages of the former in terms of flexibility are far outweighed by the sacrifice of degrees of freedom. Therefore, regarding the selection of the dependent variable, we selected each input excess as the dependent variable for the individual SFA regression.

For each input slack s_{mj}, we defined the following:

$$\begin{aligned} & s_{mj} = x_{mj} - X_m\lambda \\ & s_{mj} \geq 0 \\ & m = 1, \cdots, M \\ & j = 1, \cdots, J, \end{aligned} \tag{2}$$

where s_{mj} denotes the jth DMU using the mth input in the slack of stage 1, and $X_m\lambda$ is the optimal projection of x_{mj} on the output vector y_j.

For each individual SFA regression, we used the following form of interpretation:

$$\begin{aligned} & s_{mj} = f^m\left(z_j; \beta^m\right) + \nu_{mj} + u_{mj} \\ & Z_j = \left[Z_{1j}, \dots, Z_{Q_j}\right] \\ & m = 1, \cdots, M \\ & j = 1, \cdots, J, \end{aligned} \tag{3}$$

where Q denotes the number of observables, Z_j are external environmental variables and the independent variables in the SFA regression model, β^m denotes the parameter vectors, $f^m\left(Z_j;\ \beta^m\right)$ denotes the deterministic feasible slack frontiers, and $\nu_{mj} + u_{mj}$ are the mixed error terms.

In this study, we selected to use the stochastic cost frontier type of SFA regression [36]. We assumed that ν_{mj} represented statistical noise (random factors) and $u_{mj} \geq 0$ represented managerial inefficiency and, in the SFA regression model, the effect of statistical noise on input slack variables and the effect of managerial inefficiency on input slack variables, respectively.

We made distribution assumptions for ν_{mj} and u_{mj} separately, assuming that ν_{mj} obeyed normal distributions, that is, $\nu_{mj} \sim N\left(0, \sigma^2_{\nu m}\right)$, assuming that u_{mj} obeyed normal distribution truncated at zero point: $u_{mj} \sim N^+\left(\mu^m, \sigma^2_{um}\right)$. Then, we were able to use the likelihood ratio to test the existence of u_{mj}. That is, if the original hypothesis of the existence of u_{mj} was not rejected in the SFA model by the likelihood ratio test, then there was no need to use SFA regression, and Tobit regression could be used directly [35].

In the stage-2 SFA regression, we obtained parameter estimates, such as $(\widehat{\beta}^m,\ \widehat{\mu}^m,\ \widehat{\sigma}^2_{\nu m},\ \widehat{\sigma}^2_{um})$, the size and direction of each reflected the different effects from each source. Next, we adjusted the DMUs' inputs by the parameter estimates to accommodate the adverse effects of different environmental changes and random noise. The aim was to level the playing field before repeating the DEA analysis [35]. To avoid the negative impact of excessive downward adjustment (negative values are contrary to realistic DMU activity), we referred to Fried et al. [35] and uniformly used upward adjustment to benefit all DMU input values after adjusting them, as far as was possible, to a relatively favorable environment and relatively beneficial random noise. We constructed the

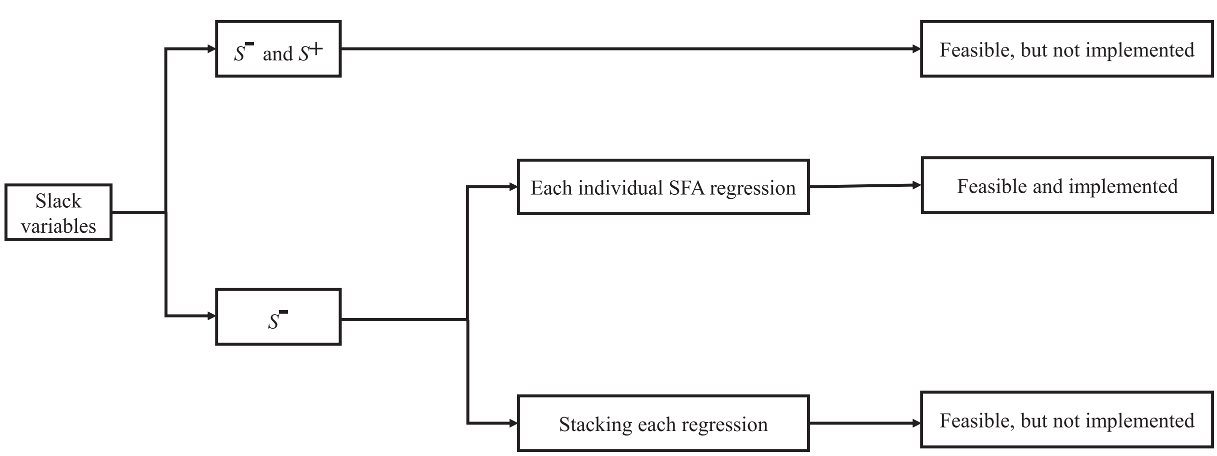

Fig. 2. Selection of dependent variables for SFA regression.

following DMU-adjusted input formula:

$$
\begin{aligned}
& x_{mj}^{A} = x_{mj} + \left[max_j\{z_j\widehat{\beta}^{m}\} - z_j\widehat{\beta}^{m}\right] + \left[max_j\ \{\ \widehat{v}_{mj}\ \} - \widehat{v}_{mj}\right] \\
& m = 1, \cdots, M \\
& j = 1, \cdots, J,
\end{aligned} \tag{4}
$$

where x_{mj}^{A} represents the adjusted input quantity, x_{mj} is the original input quantity, and $max_j\{z_j\widehat{\beta}^{m}\} - z_j\widehat{\beta}^{m}$ and $max_j\{\widehat{v}_{mj}\} - \widehat{v}_{mj}$ denote the adjustment of a DMU to the same external environment and the same nonanthropogenic state, respectively. Therefore, the number of upward adjustments $max_j\{z_j\widehat{\beta}^{m}\} - z_j\widehat{\beta}^{m} + max_j\{\widehat{v}_{mj}\} - \widehat{v}_{mj}$ is relatively small for DMUs with a relatively poor external environment or nonanthropogenic relatively unfavorable. In contrast, the amounts of upward adjustments are relatively large for DMUs with a relatively beneficial external environment or nonanthropogenic relatively favorable.

Next, we separated the statistical noise ν_{mj} and the management inefficiency u_{mj} to achieve Eq. (4). We referred to Jondrow et al. [37] to separate the mixed error term in Eq. (3), and we derived the estimation equation for statistical noise:

$$
\begin{aligned}
& \widehat{E}\ \left[v_{mj}\ \middle|\ v_{mj} + u_{mj}\right] = s_{mj} - z_j\widehat{\beta}^{m} - \widehat{E}\ \left[\ u_{mj}\ \middle|\ v_{mj} + u_{mj}\right] \\
& m = 1, \cdots, M \\
& j = 1, \cdots, J
\end{aligned} \tag{5}
$$

We found $\widehat{E}\left[\nu_{mj}\middle|\nu_{mj}+u_{mj}\right]$ depending on $\widehat{E}\left[u_{mj}\middle|\nu_{mj}+u_{mj}\right]$, where $z_j\widehat{\beta}^{m}$ is the estimation of each environment variable and can be calculated from the estimation of the parameter β^{m}, and Eq. (2) provides s_{mj}; therefore, in order to implement Eq. (5), we needed to derive $\widehat{E}\left[u_{mj}\middle|\nu_{mj}+u_{mj}\right]$.

Jondrow et al. [37] used stochastic production frontier, that is, the mixing error term was $\nu_{mj} - u_{mj}$; however, we used stochastic cost frontier, that is, the mixing error term was $\nu_{mj} + u_{mj}$. Therefore, we could refer to Jondrow et al.'s [37] methodology of derivation to isolate the estimation formula for the management inefficiency:

$$
\begin{aligned}
& \widehat{E}\left[u_{mj}\ \middle|\ v_{mj} + u_{mj}\ \right] = \\
& \frac{\widehat{\sigma}_{um}\widehat{\sigma}_{vm}}{\sqrt{\widehat{\sigma}_{um}^{2} + \widehat{\sigma}_{vm}^{2}}}\left[\frac{\phi\left\{\dfrac{\left(\widehat{v}_{mj} + \widehat{u}_{mj}\right)\dfrac{\widehat{\sigma}_{um}}{\widehat{\sigma}_{vm}}}{\sqrt{\widehat{\sigma}_{um}^{2} + \widehat{\sigma}_{vm}^{2}}}\right\}}{\Phi\left\{\dfrac{\left(\widehat{v}_{mj} + \widehat{u}_{mj}\right)\dfrac{\widehat{\sigma}_{um}}{\widehat{\sigma}_{vm}}}{\sqrt{\widehat{\sigma}_{um}^{2} + \widehat{\sigma}_{vm}^{2}}}\right\}} + \frac{\left(\widehat{v}_{mj} + \widehat{u}_{mj}\right)\dfrac{\widehat{\sigma}_{um}}{\widehat{\sigma}_{vm}}}{\sqrt{\widehat{\sigma}_{um}^{2} + \widehat{\sigma}_{vm}^{2}}}\right] \\
& \widehat{\sigma}_{m}^{2} = \widehat{\sigma}_{um}^{2} + \widehat{\sigma}_{\nu m}^{2} \\
& \widehat{\gamma}_{m} = \frac{\widehat{\sigma}_{um}^{2}}{\widehat{\sigma}_{um}^{2} + \widehat{\sigma}_{\nu m}^{2}},
\end{aligned} \tag{6}
$$

where $\widehat{\nu}_{mj} + \widehat{u}_{mj}$ denotes the estimated value of the mixed error term, ϕ denotes the probability density function of the standard normal distribution, and Φ denotes the cumulative distribution function of the standard normal distribution.

2.4. Third stage: Repetition of the first-stage operation

We obtained the adjusted inputs, which are x_{mj}^{A}, through the second-stage analysis. The output of the third stage remained the same as that of the first stage, after which we repeated the evaluation of the first stage and obtained the third-stage evaluation of the DMU. Compared with the initial, first-stage DMU value, that obtained in the third stage cleared the impact of the external environment and statistical noise.

2.5. Input and output variables

We used data from 26 countries for 21 years (2000–2020) to assess solar PV power efficiency from an economic perspective. The most commonly used variables regarding a country's economic activity are capital and labor, which are usually used as input variables in the production function of the economic model [38–40]. Topcu et al. [41] analyzed 124 countries with different income levels between 1980 and 2018 using a panel vector autoregression method and found that gross capital formation (% of GDP) positively affected economic growth in high-income countries but had a negative effect in low-income countries. Onyinye et al. [42] and Satti et al. [43] found a bi-directional relationship between gross capital formation and economic growth. Considering that the direction of the impact of gross capital formation on economic growth is different in countries with different levels of income, we selected gross capital formation as one of the input indicators.

According to the World Development Indicators, labor is the supply of labor in an economy used to produce goods and services, and it includes people who are employed, unemployed but looking for work, and first-time jobseekers [44]. These three groups of people have different directions of influence on economic growth, so we selected labor as an input indicator. The cumulative number of solar PV patents is used as a proxy for technological innovation in solar PV generation, which is crucial in addressing energy security, access, and climate change. The basic elements of the solar PV generation system are PV panels, cables, hard disks for mounting or fixing, inverters, chargers, discharge controllers, batteries, and other components [45], and in this study the totality of basic elements is represented by solar PV installed capacity. Solar PV installed capacity and solar PV generation are the most basic indicators of solar PV power efficiency. Therefore, we selected solar PV installed capacity, the cumulative number of solar PV patents, gross capital formation, and labor as input variables and solar PV generation as the output variable. Table 2 summarizes all the variables and sources used for the three-stage DEA.

2.6. External environmental variables of solar PV power efficiency

External environmental variables affect the solar PV power efficiency of each country differently (see Table 2 for sources of external environment variables). An extensive literature review shows that the proportion of the urban population in the total population, GDP per capita, and carbon dioxide emissions all affect solar PV power efficiency.

The proportion of the urban population in the total population has an essential impact in terms of energy resource structure and lifestyle, and as urbanization accelerates, it affects different types of power consumption [49–51]. GDP per capita is used to measure the level of economic development of different countries; the level of economic growth

Table 2
All variables used for the three-stage DEA model and their data sources[a].

Type	Variable (unit)	Model	Data source
Input	Solar PV installed capacity (MW)	BCC-DEA	BP [46]
	The cumulative number of solar PV patents (numbers)	BCC-DEA	IRENA INSPIRE [47]
	Gross capital formation (% of GDP)	BCC-DEA	World Bank [44]
	Labor (population)	BCC-DEA	World Bank [44]
Output	Solar PV generation (GWh)	BCC-DEA	IEA [48]
Environment variables	The proportion of the urban population in the total population (%)	SFA	World Bank [44]
	GDP per capita ($)	SFA	World Bank [44]
	Carbon dioxide emissions (million tons)	SFA	BP [46]

Note: [a] Zero data are reported for countries in periods for which data have not been published.

determines the country's ability to invest in solar PV generation infrastructure development, which can affect solar PV power efficiency [52–54]. Countries with more significant carbon emissions have more responsibility for reducing such emissions and achieving sustainable development. They also have relatively greater expectations of non-fossil-fuel energy generation, which will also increase the level of attention given to solar PV generation; furthermore, more government policies and researcher input will influence solar PV power efficiency [55–57].

3. Results and discussion

This section first summarizes the results of each phase and then compares and analyzes the results of the first and third phases.

3.1. The first stage: Initial solar PV power efficiency results

In the first stage, we calculated the solar PV power efficiency of 26 countries from 2000 to 2020 using the BCC–DEA model. The results are presented in Fig. 3, which shows solar PV power efficiency scores over 21 periods in the 26 countries evaluated. The overall characteristics of these countries between 2000 and 2020 fluctuate, either rising and then falling or falling and then rising, and there is an overall average solar PV power efficiency score of 0.762, indicating that there is still much room for improvement. The average solar PV power efficiency in these countries fell to a minimum value of 0.686 in 2007 and reached a maximum value of 0.906 in 2020. The average solar PV power efficiency score fluctuated around 0.8 for the five years from 2000 to 2004 and decreased for the four years from 2004 to 2007, indicating that the global financial crisis of 2007–2008 had a significant impact on the economy and on energy. According to Bartlett et al. [58], the financial crisis increased the PV industry's costs and reduced investments in the PV industry. The type and duration of PV investment directly affected PV installations, resulting in a significant decrease in PV demand and, ultimately, a decline in solar PV power efficiency scores. Solar PV power efficiency started to rise slowly in 2008, indicating that countries have been making different efforts toward the development of solar PV power efficiency since 2008.

The results show that from 2000 to 2020 the average solar PV power efficiency score of Belgium, Denmark, Greece, Italy, Portugal, Sweden, the United Kingdom, Israel, Egypt, and the Philippines exceeded 0.8, indicating that these countries experienced slow and sustained simultaneous growth in solar PV generation in line with economic development and meeting economic needs. Most of the countries mentioned above, with an average score above 0.8 during the assessment period, are from the European Union and set clear goals early on, such as working together to curb greenhouse gas emissions, investing in renewable energy, and actively participating in the energy transition. The 2008 European Energy and Climate Change Policy was defined and set by the European Council and Parliament with the goal of reducing greenhouse gas emissions by 30% through international agreements and significantly increasing the use of renewable energy sources, tripling renewable energy use by 2020 [59].

Second, countries such as Canada, Mexico, the United States, Austria, France, Germany, Spain, Morocco, Australia, India, and Japan have performed poorly, with scores below the average. Although these countries are also actively improving PV technology and energy transition, the contribution of solar PV generation is smaller than required, given their levels of economic development. According to World Development Indicators [44], the weighted average of the percentage of total electricity production from renewable sources (excluding hydroelectricity and including geothermal, solar, tides, wind, biomass, and biofuels) from 2000 to 2015 was as follows: Canada (2.72%), Mexico (3.72%), the United States (3.68%), France (2.35%), Morocco (2.54%), Australia (3.22%), India (2.74%), and Japan (2.86%). However, in countries with a better average score, the contribution made by solar PV generation is greater. For example, Honrubia-Escribano et al. [60] found that the contribution of PV to electricity demand coverage is increasing in Belgium, Greece, Italy, and the United Kingdom. In Italy and Greece, in particular, solar PV currently meets more than 7% of national electricity demand [61].

Third, despite an apparent surge in solar PV generation between 2019 and 2020 in China and South Korea, these countries have average scores of 0.463 and 0.536, respectively, which are much lower than those of other countries. Dependence on fossil fuels is particularly evident in China and South Korea [62,63]. In addition, the imbalance between power supply and demand in China and the lack of power transition grids have caused a significant curtailing solar power generation [64]. The Korean government decided to introduce a renewable energy portfolio standard program in 2012, and solar energy has begun to draw the attention of Korean electricity suppliers [65].

As shown in Fig. 3, the vast majority of countries had a score of 1 in 2020, meaning that they reached the production frontier side, generating more solar PV and smaller economic burdens with relatively small inputs. During the study period, the year 2020, the year which saw the highest growth in solar PV generation, was also the only year with negative growth in labor. Greenhouse gas emissions have been identified as a major threat to human civilization [66], and in order to control the effects of climate change, fundamental reductions in such emissions, particularly those from power generation systems, are needed [67]. The use of solar PV offers the benefit of reducing greenhouse gas emissions [45]. Over recent decades, the share of PV in the global electricity supply has been increasing [68,69]. In addition, the COVID-19 pandemic in 2020 had a substantial impact on the economies of countries around the world. According to World Development Indicators [44], COVID-19 led to negative GDP growth in 2020 (the United States (-3.40%), Mexico (-8.17%), Belgium (-5.68%), Denmark (-2.06%), Germany (-4.57%), Greece (-9.02%), Italy (-9.03%), the Netherlands (-3.80%), Portugal (-8.44%), Israel (-2.15%), Morocco (-6.29%), India (-6.60%), and Japan (-4.51%)). The relationship between national economies and health is becoming increasingly important. Solar PV generation is less polluting to the environment and more health-friendly, and technological innovations in PV have reduced its cost and economic burden [70]. As a result, solar PV generation surged in 2020, with solar PV power efficiency reaching 1. Compared to countries on the production frontier side, countries such as Canada, Czech Republic, France, Sweden, and the Philippines lagged far behind in 2020, with relatively low solar PV power efficiency scores and relatively large fluctuations in the time series. In the United States, China, Japan, and Germany, there was an overall upward trend toward solar PV power efficiency, and the solar PV power efficiency of Denmark was the most stable, essentially remaining at around 1.

According to the World Bank classification, the gross national income per capita in high-income countries is at least $12,376 [71]. Of the 26 countries in this study, 20 are high-income countries, among which South Korea has a relatively poor solar PV power efficiency score. Of the two upper-middle-income countries, China has the worse solar PV power efficiency scores. Of the four lower-middle-income countries, Morocco has the worst solar PV power efficiency score. Looking at the average solar PV power efficiency for each country over the 21 years analyzed, we found that the top 10 countries were mainly high-income: (1) Denmark, (2) Egypt, (3) Greece, (4) Israel, (5) Belgium, (6) Portugal, (7) the Philippines, (8) Sweden, (9) Italy, and (10) the United Kingdom. The solar PV market has grown significantly due to falling installation costs and various government subsidy measures, with most of the growth concentrated in relatively affluent and highly educated, high-income households, while lower-middle-income households are lagging behind [72,73]. This growth trend is also particularly pronounced in high-income countries, where there is a relatively larger proportion of high-income households. High-income countries have higher productivity and a higher quality of life and are well positioned to reconcile economic development with solar PV generation. The two countries at

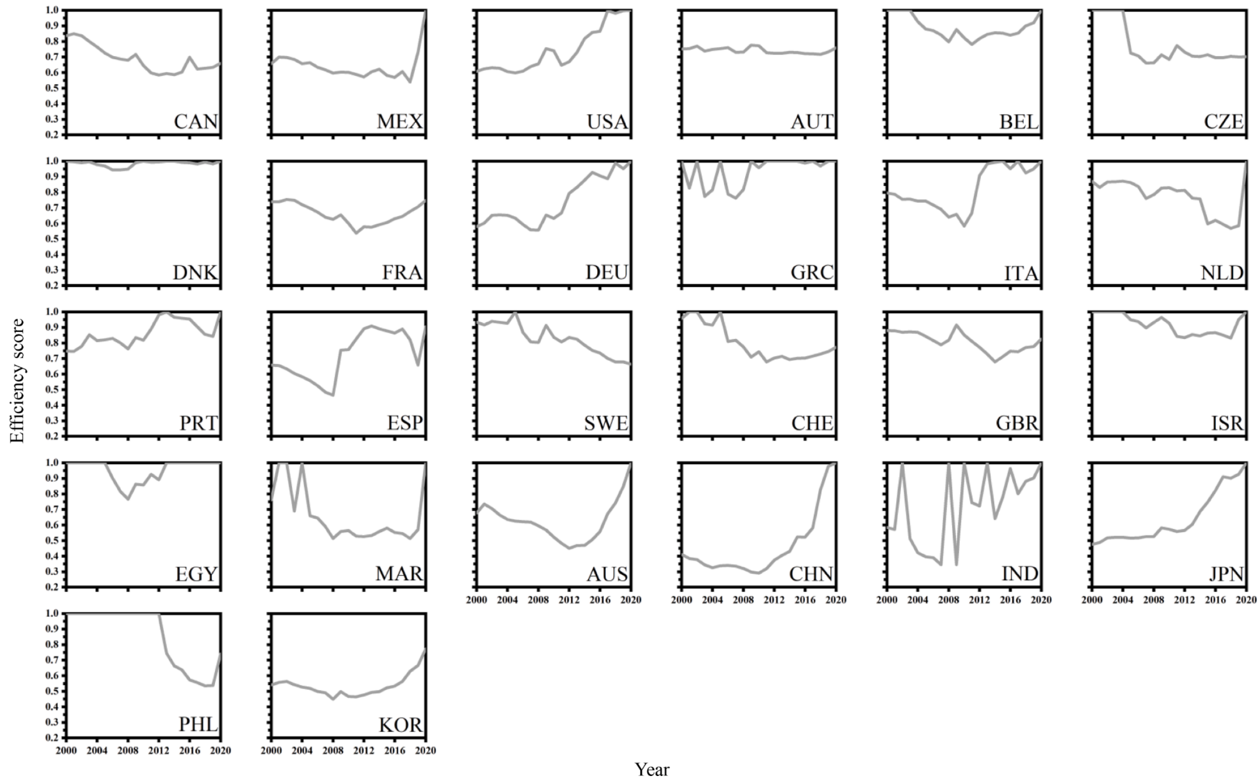

Fig. 3. The change graph of solar PV power efficiency in the first stage. CAN: Canada, MEX: Mexico, USA: United States, AUT: Austria, BEL: Belgium, CZE: Czech Republic, DNK: Denmark, FRA: France, DEU: Germany, GRC: Greece, ITA: Italy, NLD: Netherlands, PRT: Portugal, ESP: Spain, SWE: Sweden, CHE: Switzerland, GBR: United Kingdom, ISR: Israel, EGY: Egypt, Arab Rep., MAR: Morocco, AUS: Australia, CHN: China, IND: India, JPN: Japan, PHL: Philippines, KOR: Korea, Rep..

the bottom of the ranking were (25) South Korea and (26) China; as shown in Fig. 3, the change graph of solar PV power efficiency in South Korea floated around 0.5 until 2018, with better development from 2019 to 2020. The value of solar PV power efficiency in China, which was basically within 0.4 before 2010, may be related to China's crude production model, which is accompanied by redundant PV cost inputs and excessive government support. After 2010, the curve moved to the upper right (production frontier), which may be related to the change in production model brought about by the Beijing Olympics in 2008 and Shanghai World Expo in 2010.

3.2. The second stage: SFA regression results

We used the slack variables of each of the four input variables in the first stage as the four dependent variables in the second stage. Three external environmental variables (the proportion of the urban population in the total population, GDP per capita, and carbon dioxide emissions) were used as independent variables. The SFA regression results are shown in Table 3.[1]

Table 3 shows that the value of each likelihood ratio test of the one-sided error is greater than the critical value of the mixed chi-squared distribution test and passes the 1% significance test, indicating that the SFA model is valid. Each gamma ($\widehat{\gamma}_m = \frac{\widehat{\sigma}_{um}^2}{\widehat{\sigma}_{um}^2 + \widehat{\sigma}_{vm}^2}$) is greater than 0.7 and close to 1, indicating that management inefficiency is the main factor affecting solar PV power efficiency. The SFA model can be used to remove the effects of the external environment and statistical noise.

When we analyze the relationship between the external environment variables and slack variables, we generally determine the positive or negative relationship between them using the positive or negative regression coefficient. The negative regression coefficients indicate that an increase in external environmental variables caused a decrease in slack variables, which increased solar PV power efficiency. The positive regression coefficients indicate that an increase in external environmental variables brought about more input slack, leading to a decrease in solar PV power efficiency. The effects regarding each of the external environmental variables are as follows:

(1) The proportion of the urban population in the total population has a 1% significant positive or negative correlation with each of the slack variables. That is, as the proportion of the urban population in the total population increases, the input of solar PV installed capacity and the cumulative number of solar PV patents increase correspondingly, and the input of gross capital formation and of labor decreases correspondingly. Among the 26 countries considered in this assessment, most were high-income, and the level of urbanization was relatively high. The corresponding solar PV installed capacity and the cumulative number of solar PV patents developments have been able to develop in parallel. Along with accelerated urbanization, a large amount of solar PV installed capacity and many of the cumulative number of solar PV patents are being put in increasing, resulting in a surplus of inputs, which adversely affects solar PV power efficiency. While the proportion of the urban population in the total population has grown in quantity, the quality of the urbanization process has received little attention. The large influx of people into cities results in a large labor force; capital and GDP are required to grow in tandem, inevitably leading to a shortage of inputs for

[1] See Tables S1–S4 of Supplementary data for the robustness test of all dependent variables. The robustness tests have a varying number of independent variables. Among the four combinations, the proportion of the urban population in the total population and GDP per capita are statistically significant and robust. Carbon dioxide emissions have some wobbles. However, overall, Tables S1–S4 pass the robustness test.

Table 3
SFA estimation results.

Dependent variable	Solar PV installed capacity	The cumulative number of solar PV patents	Gross capital formation (% of GDP)	Labor
Constant term	−4313.26 (-4312.85)***	−13034.16 (-13035.27)***	0.12 (5.83)***	1.46×10^8 (1.42×10^8)***
The proportion of the urban population in the total population	18.11 (14.44)***	130.55 (260.63)***	-3.26×10^{-3} (-4.37)***	-2.66×10^6 (-6.81×10^5)***
GDP per capita	0.03 (8.61)***	1.15×10^{-4} (0.04)	2.00×10^{-6} (3.2)***	−174.15 (-2.03)**
Carbon dioxide emissions	0.13 (2.12)**	0.5 (45.81)***	-1.50×10^{-5} (-1.95)	40564.65 (17.29)***
Sigma-squared	2.11×10^7 (2.11×10^7)***	7.82×10^7 (7.82×10^7)***	85.55 (51.19)***	1.10×10^{16} (1.10×10^{16})***
Gamma	0.9999 (1.63×10^5)***	0.9999 (2.30×10^6)***	0.9999 (7.75×10^6)***	0.7477 (37.39)***
Log likelihood	−5000.10	−5389.72	−1608.91	−10722.43
Likelihood ratio test of the one-sided error	354.42***	290.59***	128.33***	38.99***

Note: Values in bracket denote *t*-statistics. *, **, and *** represent significant levels at 10%, 5%, and 1%, respectively.

gross capital formation and labor. At the same time, the urban population's demand for a quality of life characterized by high energy consumption will stimulate an increase in solar PV power efficiency. There is a positive impact on solar PV power efficiency.

(2) As for GDP per capita, although all coefficients on solar PV installed capacity, the cumulative number of solar PV patents, and gross capital formation were positive, the effects are insignificant. The coefficient on labor was negative and had a significant effect, indicating that GDP per capita was positively correlated with solar PV power efficiency. The growth of GDP per capita indicates the development of the country's economy, the growth of people's income, and the change in people's lifestyles. As a result, people's access to energy and the way they consume it have essentially changed with the increase in GDP per capita, gradually transforming from fossil energy generation to renewable energy generation, especially in the solar PV power sector. The cost of solar PV modules has fallen by about 90% since the end of 2009 [74], accompanied by falling costs, technological advances, enhanced government deployment, and people's pursuit of a high quality of life, all of which have raised solar PV power efficiency.

(3) As for carbon dioxide emissions. the coefficients of solar PV installed capacity, the cumulative number of solar PV patents, and labor were all positive, while the effect on gross capital formation was negligible. These findings show that an increase in carbon dioxide emissions increases the inputs of solar PV installed capacity, the cumulative number of solar PV patents, and labor, while it decreases solar PV power efficiency. In this analysis, the energy consumption structure varied significantly from country to country, but most of the 26 countries' economies were mainly developed through fossil energy consumption, which emits large amounts of carbon dioxide. Therefore, accelerating the energy mix transition of countries and reducing carbon dioxide emissions will positively impact solar PV power efficiency. Ren et al. [75] and Wang et al. [76] found that an increase in the cumulative installed capacity of solar PV had a positive effect on carbon dioxide emissions reduction in China, meaning that the active development of the solar PV generation industry will also drive down carbon dioxide emissions and thus increase solar PV power efficiency. This finding is also of significance in other countries. Therefore, there is a negative correlation between carbon dioxide emissions and solar PV power efficiency.

This SFA analysis indicates that external environmental factors affect the solar PV power efficiency of the 26 countries.

3.3. The third stage: Adjusted solar PV power efficiency results

We again used the BCC–DEA model to calculate solar PV power efficiency based on the adjusted input values in the second stage. The results are shown in Fig. 4.

Overall, after adjusted inputs, the average solar PV power efficiency score of the 26 countries is 0.957, reaching the maximum value of 0.986 in 2020 and the minimum value of 0.950 in 2006, 2007, and 2013. The solar PV power efficiency scores were below average, except from 2016 to 2020. At the national level, the adjusted solar PV power efficiency scores of all countries except China and India exceeded 0.9, which is close to the production frontier side. In particular, the United States and Austria were on the production frontier side for 13 years and 11 years, respectively. Both China and India are located in the Asian region, with large populations and abundant solar energy resources [77]. The two countries are facing both energy and environmental pressures to varying degrees, and their governments are working to develop solar PV generation to play a role in the future energy power system [78]. The Indian government provides financial support for solar PV generation projects, and the cumulative installed capacity of solar PV generation in India reached 28.18 GW by March 2019 [79]. However, one third of villages (about 600 million Indians) in India's power sector are not connected to the grid [80]. Therefore, there is an insufficient grid to carry and transport the power generated by solar PV generation, which is not conducive to the large-scale popularization of solar PV generation grid parity, resulting in India's low average solar PV power efficiency score. However, unlike in India, the development of solar PV generation in China went through an initial stage before 2013 and an expansion stage thereafter [81]. Before 2013, nearly all the installed solar PV capacity was installed in the western region, with the support of the Chinese government [82]. Because of the better resource endowment in the western region, solar PV generation capacity grew slowly in the initial stage. As shown in Fig. 4, solar PV power efficiency also grew slowly in the initial stage. However, the center of solar PV generation in China is different from the center of massive consumption of solar PV generation, meaning there is no transmission line to connect the western region with the eastern region effectively [83]. This situation has led to a serious waste of solar PV generation during the expansion stage, with waste rates in four regions, Xinjiang, Gansu, Qinghai, and Ningxia, reaching 32.23%, 30.45%, 8.33%, and 7.33%, respectively, in 2016 [84]. Fig. 4 shows that solar PV power efficiency scores also increased slowly from 2014 to 2016; although these years fall within the expansion stage, the solar PV power efficiency scores did not increase significantly, which is another reason that China's overall average solar PV power efficiency score is the lowest of the 26 countries considered.

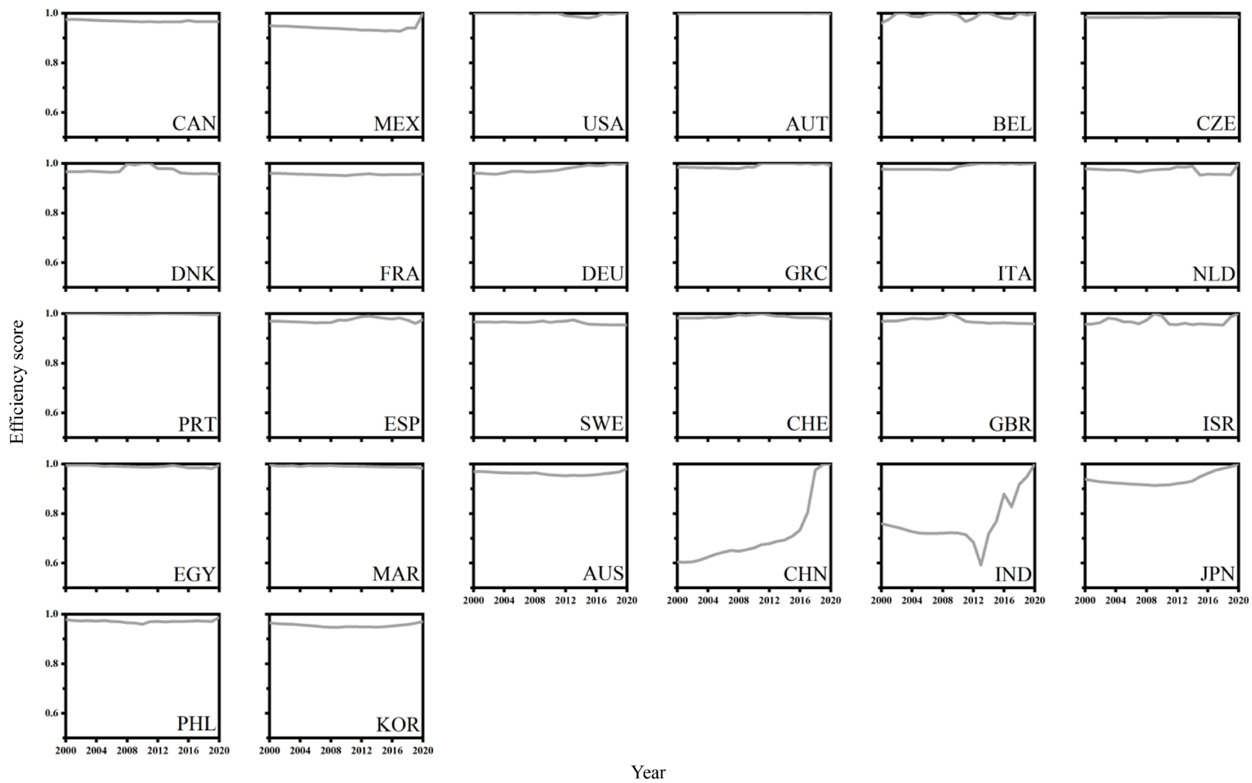

Fig. 4. The change graph of solar PV power efficiency in the third stage. CAN: Canada, MEX: Mexico, USA: United States, AUT: Austria, BEL: Belgium, CZE: Czech Republic, DNK: Denmark, FRA: France, DEU: Germany, GRC: Greece, ITA: Italy, NLD: Netherlands, PRT: Portugal, ESP: Spain, SWE: Sweden, CHE: Switzerland, GBR: United Kingdom, ISR: Israel, EGY: Egypt, Arab Rep., MAR: Morocco, AUS: Australia, CHN: China, IND: India, JPN: Japan, PHL: Philippines, KOR: Korea, Rep..

Fig. 4 shows that Austria and Portugal remained stable on the production frontier for a long time. Fina et al. [85] and Simoes et al. [86] reported on the current status of solar PV generation in Austria, assessing the deployment of solar PV generation and its optimal economic potential in terms of space, time, and shared PV. Regarding economic feasibility, solar PV generation is sufficient for large-scale development in Austria. At the same time, the Austrian government is bound to invest technically and economically to achieve at least 9.7 GW of solar PV generation by 2030 [87]. Therefore, in terms of development scale, consumption level, and economic efficiency relative to other countries, all these conditions also contribute to Austria having the best average solar PV power efficiency score. Seven countries, Belgium, Germany, the Netherlands, Israel, China, India, and Japan, all experienced different degrees and periods of increase, and finally, in 2020, their solar PV power efficiency scores all reached 1. China had the most prolonged increase, and India fluctuated relatively more than the other 25 countries in 2013 and 2016.

To more accurately analyze the solar PV power efficiency differences between the first and third stages and obtain a more intuitive sense of the changes in solar PV power efficiency scores after excluding external environmental variables, the results of the two stages are compared and analyzed in Section 3.4.

3.4. Comparison and analysis of the results of the first and third stages

Compared to the results of stage 1, Figs. 3 and 4 show that the average solar PV power efficiency score for stage 3 increased from 0.762 to 0.957, an increase of 25.5%. This finding indicates that external environmental variables did not contribute to solar PV power efficiency in the 26 countries; hence, solar PV power efficiency was underestimated in the first stage. Figs. 3 and 4 show that the overall solar PV power efficiency trend for the countries changed significantly, while the solar PV power efficiency scores for non-high-income countries changed fundamentally, except for China and India.

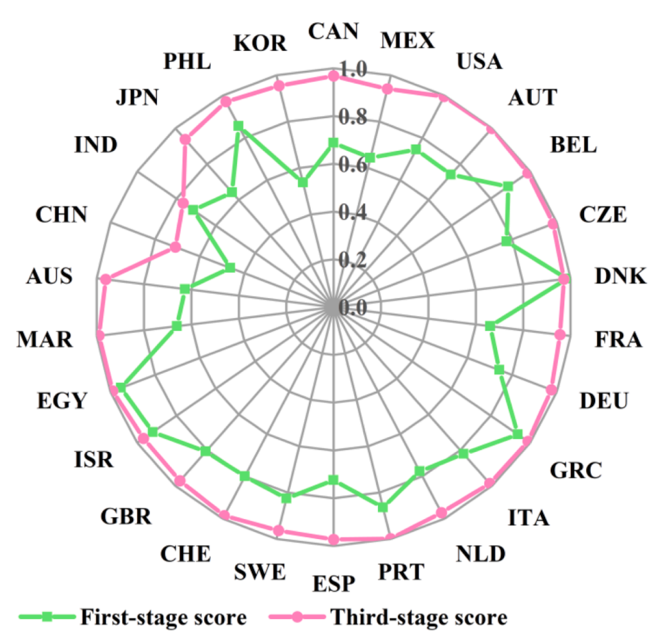

Fig. 5. Radar chart for each country's average solar PV power efficiency score in the first and third stages of the study period. CAN: Canada, MEX: Mexico, USA: United States, AUT: Austria, BEL: Belgium, CZE: Czech Republic, DNK: Denmark, FRA: France, DEU: Germany, GRC: Greece, ITA: Italy, NLD: Netherlands, PRT: Portugal, ESP: Spain, SWE: Sweden, CHE: Switzerland, GBR: United Kingdom, ISR: Israel, EGY: Egypt, Arab Rep., MAR: Morocco, AUS: Australia, CHN: China, IND: India, JPN: Japan, PHL: Philippines, KOR: Korea, Rep..

Fig. 5 shows the radar chart for each country's average solar PV power efficiency score in the first and third stages of the study period. The results for stage 3 were obtained after removing the effects of external environmental variables and statistical noise. We found that almost all countries had generally higher solar PV power efficiency scores in stage 3 than in stage 1. External environmental variables and statistical noise were non-contributing in terms of solar PV power efficiency scores, leading to an underestimation of solar PV power efficiency scores in stage 1. The reasons for this underestimation are less related to the low level of technology than to the relatively poor external environment. Compared with the scores in stage 1, Mexico, Morocco, Australia, Japan, and South Korea showed more significant increases in solar PV power efficiency scores in stage 3, with all five exceeding 0.3. This finding suggests that the external environmental factors in these five countries had a significant negative impact on solar PV power efficiency. The external environment rationing was relatively lagging because these countries have neglected external environment development while vigorously developing their productivity. This finding is similar to the conclusions of other investigators who have observed that the energy supply structures of these five countries are highly dependent on fossil fuels [88–96] and that this high dependence on fossil fuel combustion for power generation makes their carbon emissions relatively high. Thus, the external environment has significant room for improvement in Mexico, Morocco, Australia, Japan, and South Korea. Furthermore, during the study period, Mexico, Morocco, and South Korea had lower than average GDPs per capita, Japan had higher than average carbon dioxide emissions, and Australia burned fossil fuels to generate 90% of its total electricity [97]. In the second stage, we found that solar PV power efficiency was positively correlated with GDP per capita and negatively correlated with carbon dioxide emissions. Therefore, the external environments of these five countries were relatively poor overall, and the elimination of external environmental variables resulted in a significant change in solar PV power efficiency scores in the third stage.

In the third stage, Greece, Israel, Egypt, and India showed minor increases in solar PV power efficiency, from 0 to 0.05. One possible explanation for this is that the external environments in these four countries exerted only a minor influence. As a developed country, Israel has a technologically advanced market economy and a highly skilled workforce; as such, Israel itself is less influenced by the external environment. Israel has placed significant emphasis on developing its renewable energy industry and increasing its use of renewable energy. Hamed and Bressler [98] reported similar conclusions, finding that the Israeli government has developed a series of national plans and strategies for the promotion and development of renewable energy in the country to increase the use of renewable energy and energy efficiency. An exciting finding was that Greece, Egypt, and India of the external environment have a minor influence on solar PV power efficiency in our study. Although Lignite, gas, and oil-based electricity production significantly contributed to energy production in Greece, Egypt, and India [99–101], Greece adopted specific environmental and development policies set by the European Community, increasing the use of renewable energy sources [102]. In 2014, the Egyptian government launched a feed-in tariff for electricity generated by renewable energy [103]. The Indian government provides financial incentives to encourage the deployment of solar PV [101]. Moreover, by 2019, 18.51% and 32.93% of total final energy consumption in Greece and India, respectively, came from renewable energy [44]. A possible implication of this is that greenhouse gas emissions are decreasing and that the share of renewable energy generation is expanding.

Denmark's score in stage 3 (0.972) was smaller than in stage 1 (0.985), indicating that Denmark's external environment contributed to solar PV power efficiency and that its economic development created a good external environment. Matsumoto et al. [38] similarly concluded that Denmark was environmentally efficient. Our finding suggests that Denmark's solar PV generation industry structure and renewable energy consumption structure were relatively reasonable, and its technology level was relatively high, thus contributing to solar PV power efficiency.

4. Conclusions

This study used the three-stage DEA model to assess the solar PV power efficiency of 26 countries from 2000 to 2020. Solar PV installed capacity, the cumulative number of solar PV patents, gross capital formation (% of GDP), and labor were input variables, solar PV generation was the output variable, and the proportion of the urban population in the total population, GDP per capita, and carbon dioxide emissions were external environmental variables. The SFA model removed the effects of the external environmental variables and statistical noise on solar PV power efficiency. The results are summarized below.

(1) The first-stage results indicate that the solar PV power efficiency of the 26 countries considered fluctuated upward and then downward between 2000 and 2020. Belgium, Denmark, Greece, Italy, Portugal, Sweden, the United Kingdom, Israel, Egypt, and the Philippines had higher average solar PV power efficiency scores, while China and South Korea had the lowest average solar PV power efficiency scores.
(2) According to the second-stage results, external environmental variables significantly affected solar PV power efficiency. GDP per capita was positively related to solar PV power efficiency. Carbon dioxide emissions were negatively related to solar PV power efficiency. Growth of the proportion of the urban population in the total population promoted a massive increase in solar PV generation infrastructure, capital, and economic development, thus affecting solar PV power efficiency.
(3) After removing the effects of external environmental variables and statistical noise, we obtained the results for the third stage. The average solar PV power efficiency scores for the 26 countries in the third stage were generally higher than in the first stage, indicating that external environmental variables cause an underestimation of solar PV power efficiency. Differences vary by country, with Mexico, Morocco, Australia, Japan, and South Korea improving their solar PV power efficiency most significantly, all to above 0.3. Only Denmark's solar PV power efficiency decreased, by 0.013. Except in China and India, external environmental variables fundamentally changed the solar PV power efficiency of non-high-income countries' scores.

The purpose of this study was to better assess solar PV power efficiency in 26 countries in order to provide information that can be monitored and compared. The strengths and weaknesses of solar PV power efficiency in the 26 countries were identified, and further targets for improvement were set. Based on the results of this study, policymakers in the 26 countries can take several measures to improve solar PV power efficiency in their countries. For example, most of the countries with high average solar PV power efficiency scores are high-income. The observation results of high-income countries effectively help regulators and policymakers make appropriate adjustments to improve solar PV power efficiency and achieve sustainable development. In addition, we can understand how external environmental variables affect solar PV power efficiency from their positive and negative correlations with it.

Some practical aspects of this study still need to be improved on and addressed in future research. First, the inclusion of undesirable outputs could be considered when selecting output variables. It is also relevant to analyze the impact of undesirable outputs on solar PV power efficiency in the process of solar PV generation development. Specific variables need to be analyzed in further studies in the future. Second, only three external environmental variables were selected for consideration in this study. Other variables, such as the proportion of renewable energy consumption in total final energy consumption and sulfur dioxide, can be introduced in future studies. Third, other methods can also measure solar PV power efficiency, such as the three-stage SBM–DEA model [104].

CRediT authorship contribution statement

Tiantian Zhang: Conceptualization, Data curation, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Kei Nakagawa:** Conceptualization, Investigation, Validation, Writing – review & editing, Funding acquisition. **Ken'ichi Matsumoto:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared the link to my data sources in the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.120714.

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