Comparative Analysis of Operational Efficiency of Large-Scale Solar Power Generation Companies

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Abstract

This study applies data envelopment analysis (DEA) and Malmquist productivity index to evaluate the efficiency of 20 large-scale solar power generation companies in the world over ten recent years from 2011 to 2020. To clearly distinguish performance differences and analyze trends and regional features among companies, we use the super-efficiency model and global Malmquist index for the measurement of the efficiency of companies. The companies are classified into four groups by country/region. Further, we decompose the global Malmquist index to technical efficiency change and best practice gap change components. From the results of efficiency measures, this study finds that power-producing companies focusing on one country/region are operating more effectively in comparison to those that operate in different areas. The values of the global Malmquist index show that all four groups have an average index higher than 1, thereby it is confirmed that their operational efficiency has grown over the 10 years of the study period. The decomposition analysis of the global Malmquist index reveals technical efficiency change of four groups is more distinguishing than the best practice gap change. This indicates that companies' catch-up effects have improved significantly but in a rather volatile way, compared with the technological progress over time.

1. Introduction

Toward a carbon-neutral society, the use of renewable energy has been expected more than ever. After the Paris Agreement entered into force in November 2016, which is a legally binding international treaty on climate change whose goal is to limit global warming to well below 2 degrees Celsius compared to pre-industrial levels, social consciousness and momentum for green economy and growth have never been stronger. It is expected that governments, firms, and individuals take various measures to combat climate change problems and achieve the goal. Such a trend was strengthened at COP26 held in Glasgow from October to November in 2021, which concluded with the adoption of the Glasgow Climate Pact highlighting to keep warming to 1.5 degrees Celsius within reach and share the vision to become carbon neutral by 2050.

One of the promising and abundant renewable energy resources is a solar photovoltaic (PV) generation whose cumulative installed capacity has been dramatically increasing over the globe, from approximately 40 gigawatts (GW) in 2010 to over 700 GW in 2020. In particular, China leads this trend followed by India[1]. Under this circumstance, the efficient operation of solar PV companies is one of the most important factors to promoting the use of solar PV generation and the green growth of the economy with energy transition.

However, information on the operation and management of global solar PV companies, particularly from an efficiency perspective, has not been accumulated enough to the level of drawing future policy implications. Large-scale solar PV companies play an important role for achieving a society's carbon neutrality while securing a regional electricity supply. Thus, their operational efficiency and higher performance are essential

[1] Our World in Data, accessed on September 8, 2021.

for further promoting solar PV generation in an economical way. From this belief, this study assesses the operational performance of the global 20 large-scale solar PV electric power companies from 2011 to 2020 and discusses policy implications from the results.

The remainder of this paper is structured as follows. Section 2 reviews the previous studies focusing on efficiency analyses of solar PV generation companies. Section 3 explains the methodology used in this study. Section 4 presents data and results of efficiency measures. Section 5 concludes this study.

2. Literature Review

This study summarizes previous studies related to the performance analysis of solar PV generation companies.

Performance analysis using non-DEA method:

Ibarloza et al. (2018) analyzed the economic and financial performance of Spanish companies involved in photovoltaic solar energy production from the perspective of traditional ratio and index on a longitudinal population sample of around 5500 companies from the sector. The paper considered the following indexes in traditional performance analysis: net sales value, economic performance (operating profit/assets), the evolution of margin (operating profit/net sales), and evolution of turnover (net sales/assets). Guaita-Pradas and Blasco-Ruiz (2020) employed two financial models: the capital asset pricing model and historical return analysis to estimate the discount rate of solar power generation companies with a sample of 67 PV panel installation, as well as evaluate the investment in a photovoltaic plant with a capacity of 5000 kW located in eastern Spain. Kuo (2011) used four (total assets, inventory, labor rate, debt) explanatory variables in the ordinary least square (OLS) regression model along with the stochastic frontier model to estimate the cost efficiency of US public solar energy firms and suggested the linkages between cost efficiency in the industry and risk-bearing behavior of firms, change in cost efficiency and stock return. Zhang et al. (2016) analyzed the impact of subsidies to wind and solar power energy companies in China by employing the threshold regression model and identified subsidy threshold by comparing two renewable energy companies. Schabek (2020) identified the variables that are responsible for determining the financial performance of sustainable power producers in emerging markets and evaluated their performance in comparison with efficiency in the traditional energy sector. Luts et al (2021) studied the profitability determinants of unlisted renewable energy-producing companies in Germany by identifying critical variables using panel data of 783 unlisted companies from 2010 to 2018. Paun (2017) investigated the sustainability and analyzed the financial performance of renewable energy producing companies in Romania. The financial analysis shows that the renewable companies are thriving the difficult situation and are expected to become more profitable with the commitment of subsidy from governments. Rastogi (2020) employed machine learning algorithm in k-means cluster method and carried out performance analysis on renewable energy firms in India and the USA combined with financial analysis. 14 Indian companies and 14 USA companies are sorted into clusters and each cluster’s trend is analyzed, allowing vertical comparison between 2015 to 2019 and horizontal comparison between India and USA. Zhang (2015) conducted research on how different subsidy modes affects financial performance of renewable energy producing firms from 2009 to 2014. Linear programming models of direct and indirect subsidies are built to analyze the effect of them on corporate net profit. Tomczak (2019) conducted an analysis on whether electricity producing companies using renewable energy sources are in better financial situation than those using traditional energy. The analysis was based on ratio analysis of Altman's model (Altman (1968)) and cluster analysis, and the results indicate that there is no significant difference in the financial standing of the two types of companies.

Performance analysis using DEA method:

Halkos and Tzeremes (2011) built a rather complicated bootstrapped data envelopment analysis (DEA) formulation with three inputs (debt to equity, assets turnover, current ratio) and four outputs (gross profit margin, operating profit margin, return on equity return on assets) to evaluate the financial performance of the firms operating in the Greek renewable energy sector. Curtis et al (2020) combined financial ratio analysis and DEA to carry out in-depth research on business performance of 12 wind farm companies in Greece. The financial ratios analysis focused on Return on Total Assets while the DEA considering one input (capital invested) and two outputs (revenues, EBIT).

Contribution of this study:

Since solar power generation has been a vital part of renewable energy sources in the world and the efficient operations of solar power generation companies is a focal point for promoting renewable energies in the market. However, most of the existing studies that analyze operational and financial performances related to the solar PV industry have been conducted for not only power generation companies but also solar PV equipment manufacturers, investment companies, and even governments. Further, most of the studies use a single or a few conventional financial ratios for performance assessment such as return on asset (ROA), which may only investigate a limited aspect of the companies' performance. In addition, the existing papers that adopt DEA to measure the efficiency of solar power companies are mainly using basic CRS or VRS models. Meanwhile, this study applies DEA and Malmquist productivity index (MI) that evaluate the holistic measures of the efficiency of 20 large-scale solar power generation companies in the world over the recent ten years from 2011 to 2020. DEA and MI are one of the most popular methods to evaluate the holistic performance of organizations as decision-making entities. To the best of our knowledge, few previous studies examined the operational efficiency of large-scale solar power generation companies over the world using an updated data set to cover the recent period and compared them among different regions.

3. Methodology

DEA is a popular non-parametric frontier method for the holistic performance assessment of various decision-making units (DMUs), which are solar PV generation companies in this study. The basic models of DEA were first introduced by Charnes et al. (1978) and Banker et al. (1984), which correspond to the constant returns-to-scale (CRS) and the variable returns-to-scale (VRS) models, respectively. They are solved by linear programming for the efficiency measurement with several inputs and outputs.

Suppose there are n DMUs, $\mathrm{DMU}_j, j = 1, 2, \ldots, n$, for each of them m inputs $\mathrm{X}_{ij}, i = 1,2, \ldots, m$ and h outputs $\mathrm{Y}_{rj}, r = 1,2, \ldots, h$ are used for production processes. Model (1) describes the input-oriented CRS model.

$$\begin{aligned} \min \quad & \theta \\ \text{s.t.} \quad & \theta x_{ik} \geq \textstyle\sum_j \lambda_j X_{ij}, \ i = 1, \ldots, m, \\ & Y_{rk} \leq \textstyle\sum_j \lambda_j Y_{rj}, \ r = 1, \ldots, h, \\ & \lambda_j \geq 0, \ j = 1, \ldots, n. \end{aligned} \tag{1}$$

Here we consider a particular DMU denoted as "k", λ_j is a vector of structural or intensity variables for DMU_j, in which the variables are measured in the DEA model that can be any non-negative real numbers. The solution $\theta = 1$ indicates the DMU is radial efficient and $\theta < 1$ means inefficient. Though the Model (1) is described as input-oriented CRS model, it is easily reformulated as VRS model if an additional side constraint $\sum\lambda_j = 1$ is incorporated in the model. Further to note, the output-oriented model is similar to the input-oriented model, but tries to expand outputs as much as possible rather than decrease inputs. Models (1) is radial DEA model, which does not use the information of slack variables for the efficiency calculation.

Based on these models, the MI can be measured which is commonly used for comparing the efficiency of two different time periods with changed technology levels. The characteristic of the MI allows us to deal with time-series data for efficiency assessment. Figure 1 depicts a case with 2 inputs, 1 output, and 5 DMUs (A, B, C, D, F) as an example. We consider two periods case at time t and $t+1$. Line $A_tB_tC_tD_t$ is the VRS frontier at period t and line $A_{t+1}B_{t+1}C_{t+1}D_{t+1}$ is the VRS frontier at period $t+1$. Here we define F_a^b that presents the production point placed on the frontier where observed point F_a moves on a frontier at period b ($a = t, t+1, b = t, t+1$). From the setting, the MI is calculated as follows: $MI = \left[\frac{\frac{OF_{t+1}^{t}}{OF_{t+1}}}{\frac{OF_t}{OF_t^t}} \times \frac{\frac{OF_{t+1}}{OF_{t+1}^{t+1}}}{\frac{OF_t^{t+1}}{OF_t}}\right]^{1/2}$.

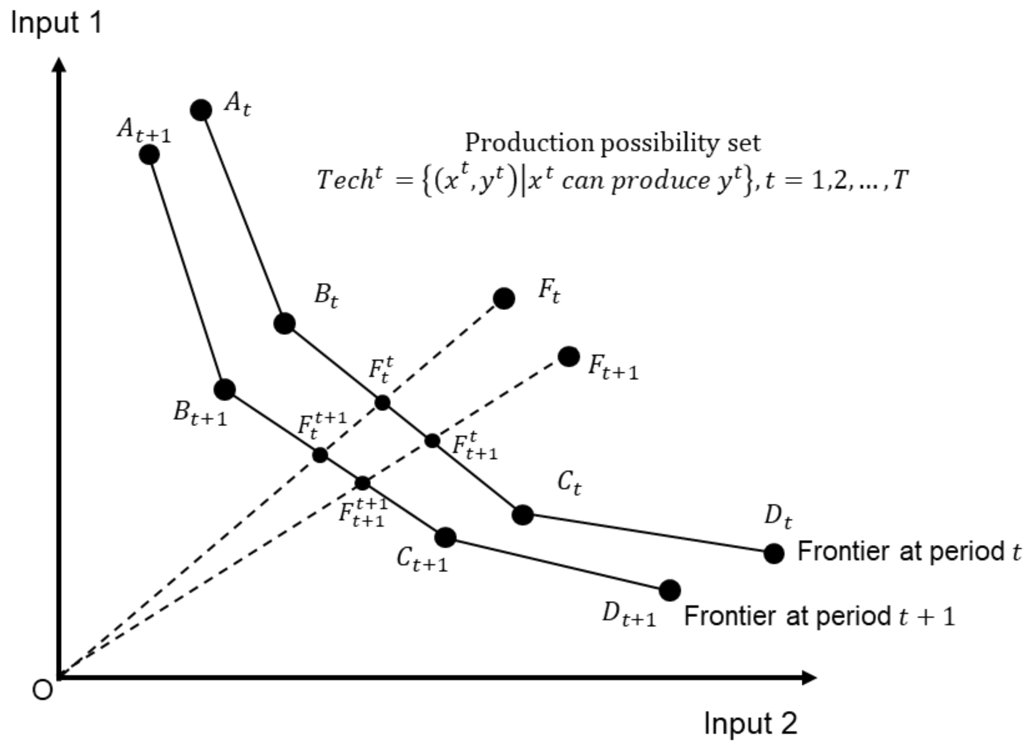

Figure 1: Two periods frontier and input-oriented Malmquist index

Further, as an extension of the standard MI, this study applies the global Malmquist index (GMI), which is proposed by Pastor and Lovell (2005) as an improvement of original MI. Kao (2010) employed DEA to calculate MI and conducted empirical analysis with GMI. Mombini et al. (2020) analyzed economic productivity improvement using a regression and GMI, and proved that the GMI enables managers to evaluate a system or organization over the periods and provide better decision-making opportunity for managers. Further, GMI was designed to overcome disadvantages of the standard MI of non-circularity, infeasibility in linear programming, and multiple measures of productivity change. All three problems are caused by the specification of adjacent period technologies, thereby the GMI solved the problems by setting a technology frontier formed by all periods rather than the previous period as in the standard MI.

Denote t as the time period of DMUs, $t = 1,2, \dots, T$, hence, there are T sets of inputs and outputs for each DMU. Here we define the specific tth period production technology, represented by the production possibility set for the standard MI, as $Tech^t = \{(x^t, y^t | x^t \; can \; produce \; y^t)\}$. The GMI is defined with the production technology of $Tech^G = Conv\{Tech^1 \cup \dots \cup Tech^T\}$, meaning that all technology frontiers including the newest one is taken into consideration. Since there is no need to calculate the efficiency under the conditions of different frontier, GMI is defined as:

$$
\begin{aligned}
GMI^{t,t+1}(X^t, Y^t, X^{t+1}, Y^{t+1}) &= \frac{DF^G(X^{t+1}, Y^{t+1})}{DF^G(x^t, y^t)} \\
&= \frac{DF^{t+1}(X^{t+1}, Y^{t+1})}{DF^t(X^t, Y^t)} \times \left\{ \frac{DF^G(X^{t+1}, Y^{t+1}) / DF^{t+1}(X^{t+1}, Y^{t+1})}{DF^G(X^t, Y^t) / DF^t(X^t, Y^t)} \right\} \\
&= \frac{TE^{t+1}}{TE^t} \times \left\{ \frac{BPG^{t+1}}{BPG^t} \right\} \qquad (2) \\
&= TEC^{t,t+1} \times BPC^{t,t+1},
\end{aligned}
$$

where $DF^G(X^t, Y^t)$ and $DF^t(X^t, Y^t)$ represent directional distance functions based on technologies $Tech^G$ and $Tech^t$, respectively. More concretely, $DF^t(X^t, Y^t) = min\{\phi > 0 | (\phi X^t, Y^t) \in Tech^t\}$ indicates efficiency measured by technology set at tth period, $DF^G(X^t, Y^t) = min\{\phi > 0 | (\phi X^t, Y^t) \in Tech^G\}$ indicates efficiency measured by technology related to whole periods. Both assumes input-oriented distance function under CRS technology. The technical efficiency difference is measured as best practice gap (BPG), and BPC is the change in BPG, whether BPC is larger or smaller than 1 indicates the distance between $Tech^G$ and $Tech^t$ is getting bigger or smaller, respectively. TEC stands for the technical efficiency change (TEC) of DMUs as described

$TEC = \frac{TE^{t+1}}{TE^{t}} = \frac{DF^{t+1}(X^{t+1},Y^{t+1})}{DF^{t}(X^{t},Y^{t})}$, wherein $TE^{t} = DF^{t}(X^{t}, Y^{t})$ is a technical efficiency at tth period. The TEC, as the change of technical efficiency, corresponds to so-called catch-up effect of the DMU.

The base period in a GMI is set in a unique way since the calculation uses all periods to construct the base period. The characteristic brings noticeable advantages to GMI. Under the standard Malmquist index measurement, when solving an empirical problem, production frontier may vary due to a short-term fluctuation in production factors in the market. That may severely influence the performance of most DMUs. That is, considering the adjacent period as a reference may lead to misunderstanding of the technology changes and the calculation of efficiency changes. The GMI, meanwhile, prevents such situation by using all data as a reference period. As shown in Figure 2, we can see, instead of varied frontiers, a global frontier is formed and F_a is shifted to the frontier at point F_a^G $(a = t, t+1)$. GMI can be calculated as $GMI = \frac{\frac{OF_{t+1}^G}{OF_{t+1}}}{\frac{OF_t^G}{OF_t}}$.

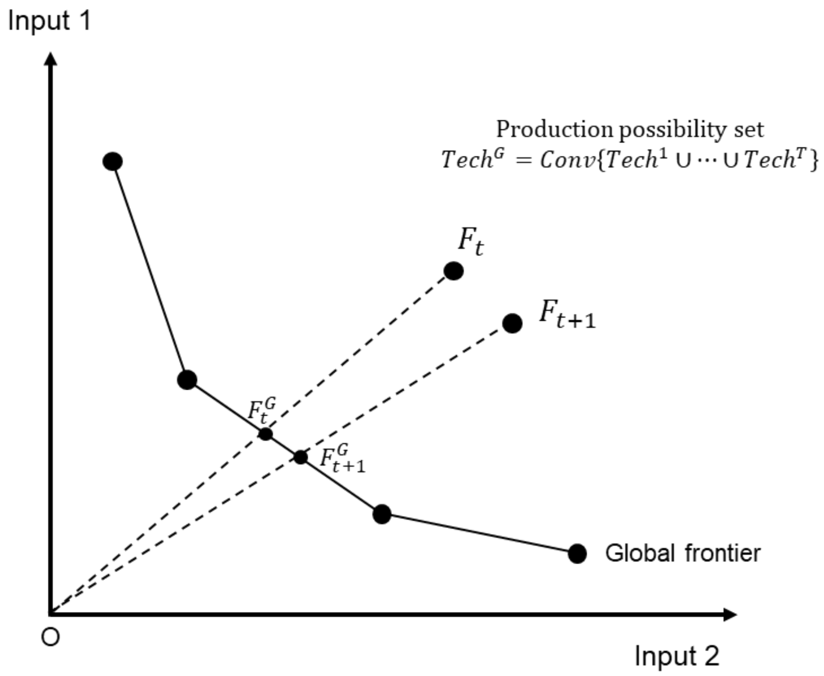

Figure 2: Global frontier and input-oriented GMI

Next, we describe a super efficiency model (SEM). As described above, CRS and VRS models focus on evaluating efficiency for different DMUs by calculating the distance between each DMU and the efficiency frontier, in which the efficient DMUs on the frontier is given efficiency value as unity. However, in some particular cases, many efficient DMUs with the efficiency of unity causes the problem in a way that the efficiency measure makes the result less revealing and consequently causes trouble in comparing efficiency. To solve the problem, Anderson and Peterson (1993) developed SEM, a modified DEA model. Unlike the VRS or CRS radial models, scores of DMUs from SEM have capability to clearly discriminate across them depending on their performance. The most advantageous feature of a SEM is that it conducts a one-step-further comparison among all the efficient DMUs without adjusting inefficient ones.

The calculation of SEM is similar to that of a CRS or VRS model, except that the DMU being evaluated will be excluded from the possible data set:

$$P(x_k, y_k) = \left\{(x, y) | x \geq \sum_{i=1,\neq k}^{m-1} \lambda_j X_{ji}, y \leq \sum_{s=1,\neq k}^{r-1} \lambda_j Y_{js}, \lambda \geq 0\right\},$$

where j $(j = 1, \dots, n)$ is DMU, X_{ji} $(i = 1, \dots, m)$ is ith input of the jth DMU, Y_{js} $(s = 1, \dots, r)$ is sth outputs of the jth DMU, and λ_j are the structural/intensity variable of jth DMU.

The calculation of super efficiency is conducted by Model (3):

$$\begin{aligned} \min \quad & \theta_k - \varepsilon(s^+ + s^-) \\ \text{s.t.} \quad & \sum_j \lambda_j Y_{js} - s^+ \geq Y_{ks},\ s = 1, \dots, r, \\ & \theta_k x_{ki} \geq \sum_j \lambda_j X_{ji} + s^-,\ i = 1, \dots, m, \\ & s^+ \geq 0, s^- \geq 0, \\ & \lambda_j \geq 0, j = 1, \dots, n, j \neq k, \end{aligned} \tag{3}$$

where s^{+}, $s^{-}$are the slack variables which are constrained to be non-negative, ε is a very small constant number set by researchers.

4. Data and Empirical Results

To compare and analyze operational efficiency of global large-scale solar power generation companies, data of 20 listed companies from different countries and regions are selected over the years 2011–2020. All data are obtained from S&P Capital IQ database, using criteria for sample companies with (1) industry classifications: "electric power by solar energy" or "electric power by wind energy", (2) company type: "public company", (3) total assets in 2020: greater than 1,000 million US dollar. This study uses six financial measures for performance assessment, consisting of three inputs and three outputs.

The three inputs are total assets, total operating expenses, and capital expenditures, which all represent basic input resources used for business activities of companies. Total assets include current assets (e.g., cash and deposit) and fixed assets (e.g., buildings, property, machine, and equipment) used in generation companies. Total operating expenses include labor costs paid for employees, rent, and marketing costs. Capital expenditures include funds to acquire, upgrade, and maintain physical assets such as those listed in total assets. Three outputs are total revenue, EBITDA, and total enterprise values. Total revenue indicates a company's business capability and scale. EBITDA is an earnings before interest, taxes, depreciation and amortization, which represents essential capability to yield profit for a company. The last one, total enterprise values, are market values calculated from share prices of a company. It often reflects the company's future growth potential expected by the market.

To conduct a comparative analysis from a perspective of geographical differences in business performance, this study divided the 20 solar power generation companies into four groups based on the following rules. Group 1 includes companies that do business in only one country/region; Group 2 includes companies that do business more than one country/region and primary office is located in North America; Group 3 is the same as group 2 but primary office is located in Europe; Group 4 is the same as Group 2 but primary office is located in the other areas. Table 1 shows year averages of the financial measures for each company classified in the four groups. The table reveals Group 4 is relatively small for all measures in averages among the four groups.

Table 1: Year averages of companies

Company Name	Group	Country/ Region	Total assets	Total operating expenses	Capital expenditures	Total revenue	EBITDA	Total enterprise values
China Longyuan Power Group Corporation Limited	1	China	20,427	2,197	2,090	3,371	2,037	16,528
Engie Brasil Energia S.A.	1	Brazil	5,754	1,267	346	2,232	1,176	9,931
Tunghsu Azure Renewable Energy Co.,Ltd.	1	China	2,355	493	155	539	64	1,051
Kong Sun Holdings Limited	1	China	1,542	105	98	144	70	818
Zhongmin Energy Co., Ltd.	1	China	696	150	56	159	39	909
Ning Xia Yin Xing Energy Co.,Ltd	1	China	1,333	151	68	195	107	1,245
Group 1 Avg.			5,351	727	469	1,107	582	5,080
Brookfield Renewable Partners L.P.	2	Canada	29,295	1,724	373	2,449	1,532	18,352
Northland Power Inc.	2	Canada	5,650	511	686	837	536	6,174
Innergex Renewable Energy Inc.	2	Canada	3,247	164	254	270	196	3,065
Boralex Inc.	2	Canada	2,350	210	132	275	166	2,142
Ormat Technologies, Inc.	2	USA	2,630	459	228	614	274	2,948
Group 2 Avg.			8,634	613	335	889	541	6,536
EDP Renováveis, S.A.	3	Spain	18,619	1,155	1,133	1,617	1,083	11,799
Terna Energy Societe Anonyme Commercial Technical Company	3	Greece	1,709	164	163	250	140	965
Falck Renewables S.p.A.	3	Italy	1,898	249	91	351	178	1,412
Voltalia SA	3	France	905	92	151	120	48	660
Albioma	3	France	1,642	373	112	481	168	1,481
Group 3 Avg.			4,955	407	330	564	323	3,263
GCL New Energy Holdings Limited	4	HongKong	4,360	243	692	423	286	2,573
Kenya Electricity Generating Company PLC	4	Kenya	3,108	214	271	315	180	941
Concord New Energy Group Limited	4	HongKong	1,932	210	225	269	90	820
Enlight Renewable Energy Ltd	4	Israel	612	29	81	40	14	501
Group 4 Avg.			2,503	174	317	262	142	1,209
Total Average			5,503	508	370	748	419	4,216

Note: All numbers are in million US dollar.

Figures 3 and 4 present overall trends of average operational efficiencies calculated by CRS model (Model 1) and VRS model (Model 1 with an additional side constraint) for companies classified in four groups. In addition, scale efficiency (SE) is calculated and the average trend is shown in Figure 5, which is the ratio of the CRS efficiency to the VRS efficiency score: $SE = \theta_{CRS}/\theta_{VRS}$. The scale efficiency measures the ability of the DMUs to operate under the most productive scale.

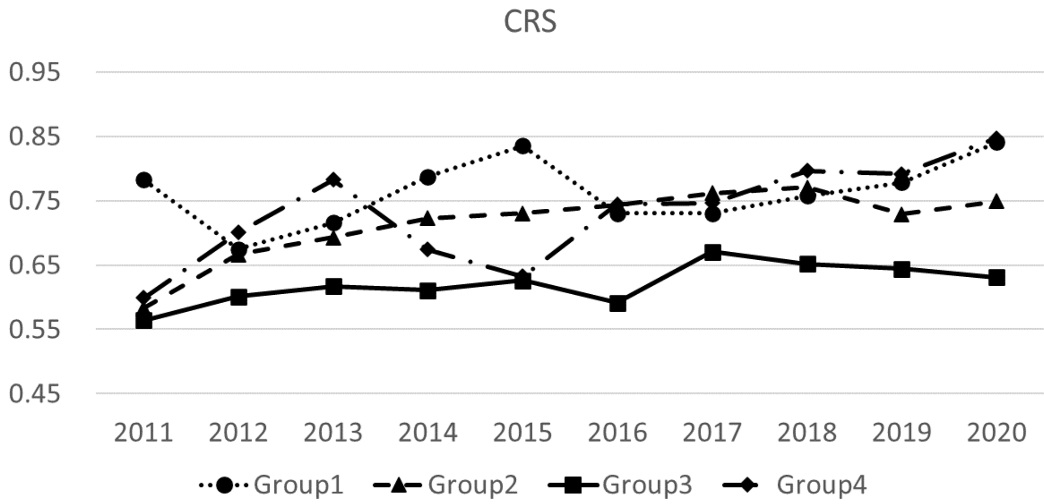

Figure 3: Average efficiency calculated by CRS model

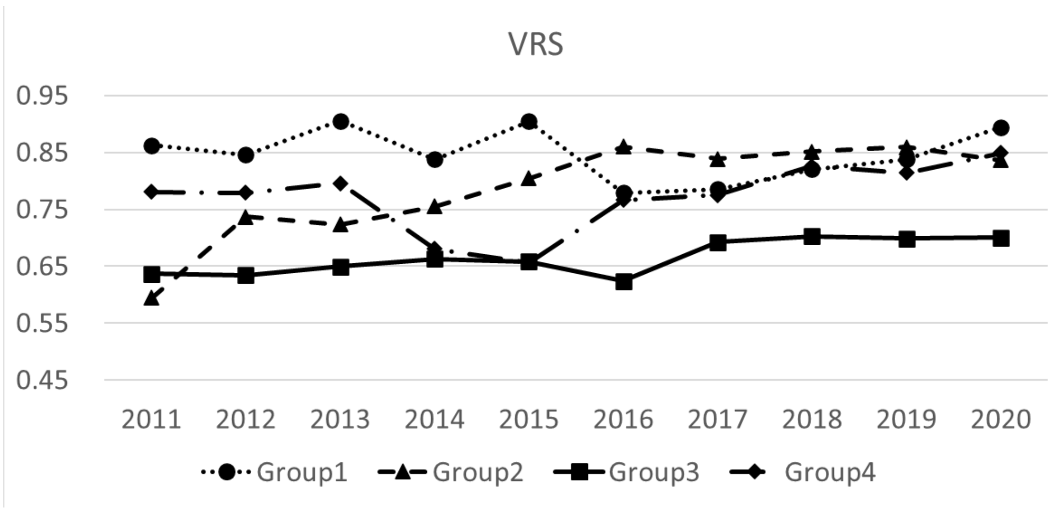

Figure 4: Average efficiency calculated by VRS model

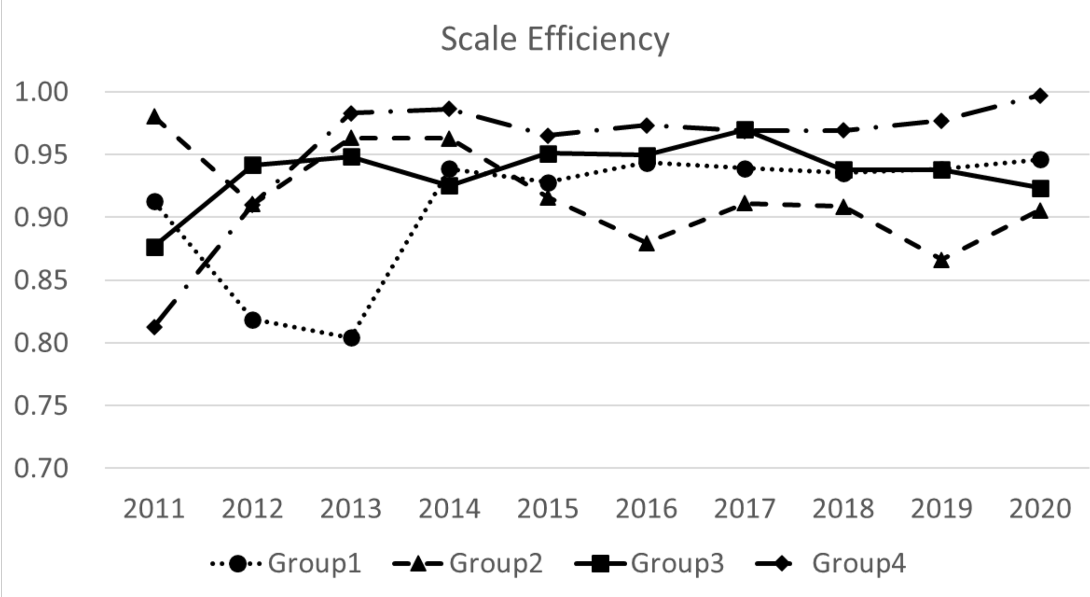

Figure 5: Average scale efficiency

By comparing the results of Figure 1 (CRS), Figure 2 (VRS), and Figure 3 (SE), we can point out four findings. First, Groups 1, 2, and 4, particularly Group 1 (companies operating in only one country/region) is generally the most efficient over the period, although the efficiency level changes over time and interacts with the other groups. The Group 1 decreases in 2016 for both CRS and VRS models but returns to an increasing trend after 2016. Second, Group 3, companies whose business area covers more than one country/region and primary office is in Europe, constantly presents lower level of efficiencies with CRS and VRS models. Third, Group 2, companies that conduct business in more than one country/region and primary office is in North America, is the lowest in CRS and VRS models, showing potential room for improvement of operational efficiency. Fourth, though the Group 3 is constantly the lowest in operational efficiencies, it is in the middle in SE as shown in Figure 5. Group 2 is the lowest performer for SE. As shown in Table 1, business scale of Group 2 is relatively large compared to the other groups, so it implies companies in Group2 may improve SE by a reduction of operational scale.

It is noted that computations of CRS and VRS models produce too many efficient DMUs. This problem is well known in studies that use conventional DEA methodology, especially when VRS is assumed on technology. The excessive efficient units are mathematically acceptable, but not acceptable from practical use of performance assessment. Thus, this paper employs SEM to remedy or alleviate the shortcoming of conventional type of CRS or VRS models.

The SEM avoids excessive efficient DMUs with efficiency score of unity. The computation results of input-oriented CRS SEM are shown in Figure 6 and the summary of the results is presented in Table 2. The results better reflect the differences in performance between efficient/inefficient DMUs in each group.

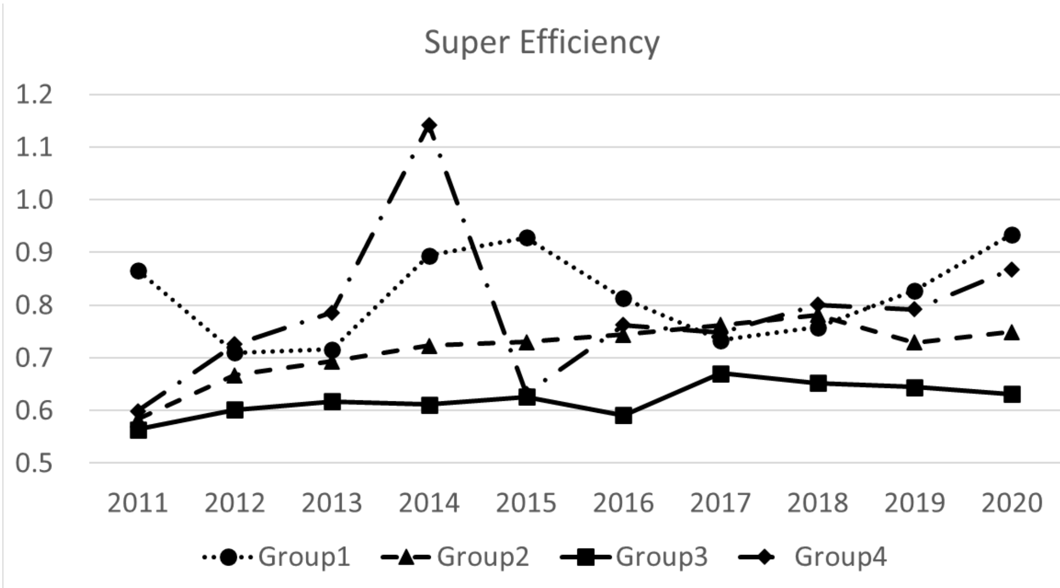

Figure 6: Average efficiency calculated by SEM

Table 2: Summary of super efficiency results

Group	1	2	3	4
Avg.	0.818	0.716	0.621	0.785

S.D.	0.299	0.129	0.077	0.396
Min.	0.133	0.520	0.327	0.308
Max.	1.604	1.056	0.745	2.873
Count	60	50	50	40

Note: Avg., S.D., Min., and Max. denote average, standard deviation, minimum, and maximum, respectively. Count is the number of samples.

From mathematical construction, SEM only reevaluates efficient DMUs in conventional CRS or VRS model. Thus, the changes seem more obvious at higher efficiency points in the figure rather than the bottom parts. For Group 1 and Group 4, the average efficiencies are still higher in all groups though their volatilities are larger than those in conventional CRS models. In particular, Group 1 presents the highest efficiency in 2020. This means that electricity generation companies focusing on only one area is operating more effectively in comparison to those that are doing business in different areas. The efficiency of Group 4 shows a feature of higher average value and higher volatility, showing large gap between maximum and minimum values during the period. In particular, it shows a high peak in 2014 but sharply decreases in 2015.

Next, we examine whether there are any significant differences among four groups in efficiency levels. We conduct Kruskal-Wallis rank sum tests to examine the differences in efficiencies. The result is presented in Table 3, which shows that the four groups are different in efficiency levels at the 1% significance level. The result also allows us to confirm the correctness of grouping principle and assure the inevitability to carry out this analysis since there are clear differences among companies of different groups.

Table 3: Kruskal-Wallis rank sum test

Source	d.f.	Chi-sq	p-value
Groups	3	19.85	0.0002

Note: d.f. denotes degrees of freedom, and Chi-sq is chi-square test statistics.

In addition to the efficiency analysis calculated by pooled data of each year and firm, we conduct efficiency analysis by using GMI to further analyze the efficiency change of DMUs over different periods. The GMI uses whole data set as a reference period. The result of temporal changes in efficiency for each group is depicted in Figure 7, and the summary of the results is described in Table 4.

Table 4: Summary of GMI

Group	1	2	3	4
Avg.	1.043	1.033	1.020	1.079
S.D.	0.259	0.109	0.098	0.274
Min.	0.214	0.703	0.886	0.401
Max.	2.119	1.287	1.325	2.068
Count	54	45	45	36

Note: Avg., S.D., Min., and Max. denote average, standard deviation, minimum, and maximum, respectively. Count is the number of samples.

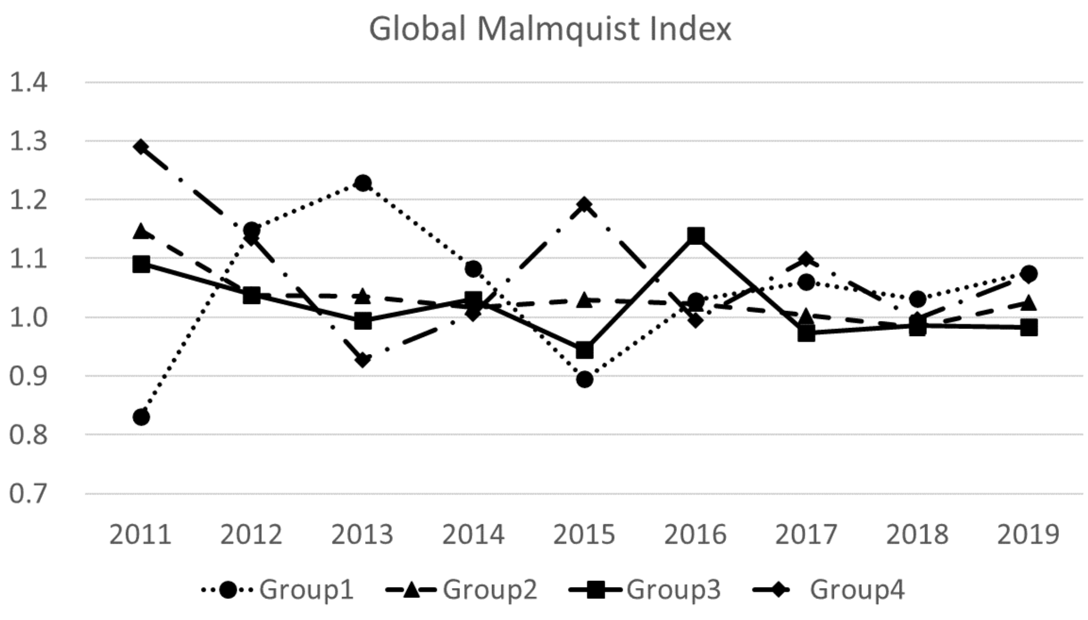

Figure 7: Average GMI

The values of GMI represent the temporal changes in total efficiency of DMUs in each group, which consists of TEC and BPC. The total efficiency improves when it is bigger than unity and decreases when it is smaller than unity. From the statistics of the results, all four groups have average index higher than 1 (Group 1: 1.043, Group 2: 1.033, Group 3: 1.020, Group 4: 1.079), thereby the operational efficiency of them has grown from 2% for Group 3 to 7.9% for Group 4 over 10 years of the study period.

In addition, it is noted that, as shown in Table 4 and Figure 9, Groups 1 and 4 have relatively higher GMI with large volatility in index. Regarding the higher total efficiency of Group 1, it is probably due to easiness in management to adapt single country/region business environment, institutions, and law. In the case of GMI calculation, it is feasible to evaluate the progress of efficiency by comparing TEC component and BPC component, respectively. Since the GMI assumes the same global technology benchmark, the larger changes in these two groups (Groups 1 and 4) can be clearly decomposed into TEC and BPC.

The TEC and the BPC are shown in Figures 8 and 9, respectively.

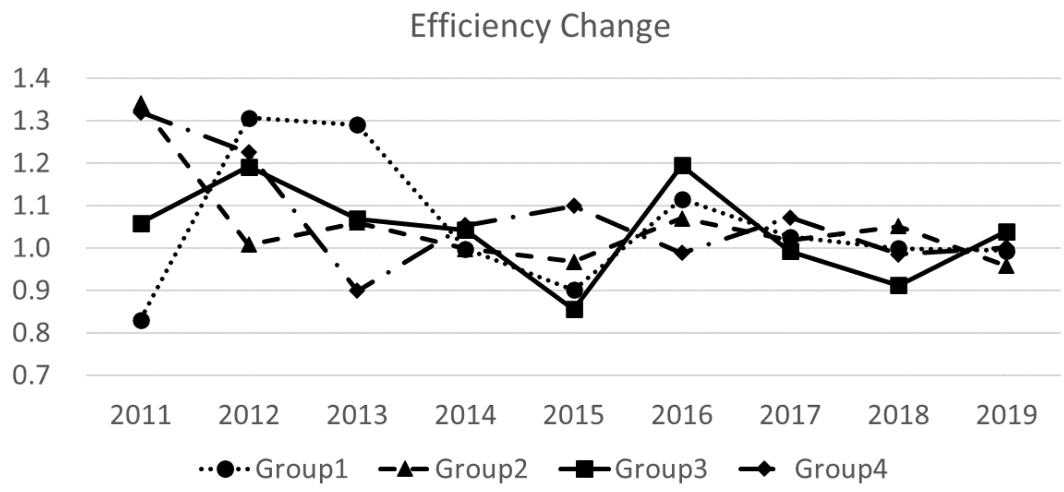

Figure 8: Average TEC

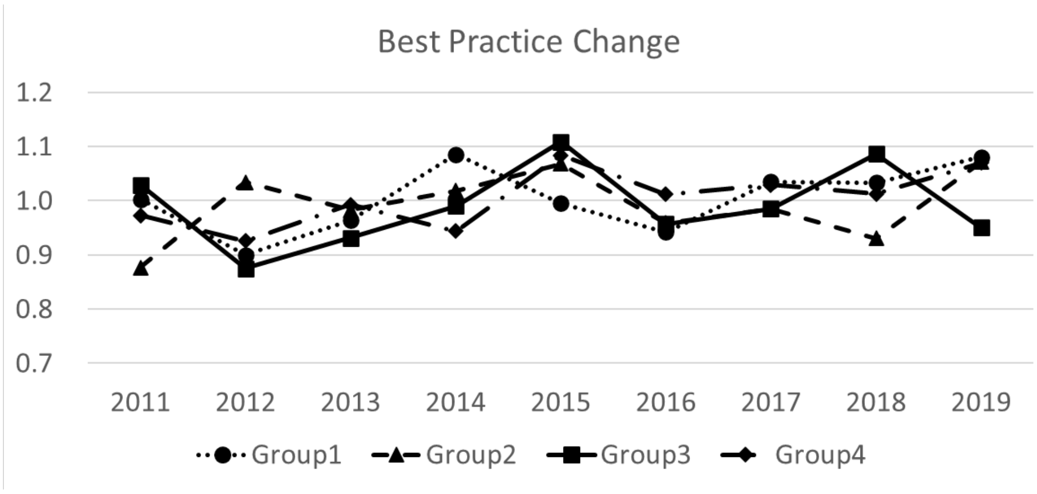

Figure 9: Average BPC

By comparing the two figures, we find that changes in TEC of four groups are more distinguishing than BPC in 2011, but the difference largely decreases in 2019. Meanwhile, variation of BPC has been stable from 2011 to 2019, although we see some fluctuations over time. This means that companies operating in one country/region or Group 1 were relatively efficient than those operating in various countries/regions, showing a rapid increase in 2012 and 2013. However, such higher efficiency advantage of Group1 disappears after 2014 and the differences among groups has shrunk to become very small. Besides, the BPC indicates that compared with the best practice frontier, companies' technology has modestly improved, and the differences in four groups are stable over time. Group 1 is slightly higher in BPC than the other groups over the period.

5. Conclusion

This study examined efficiency of 20 large-scale solar power generation companies in the world over ten recent years from 2011 to 2020 applying DEA, SEM, and GMI. We analyzed regional differences of efficiencies among companies using the measures, and decomposed the GMI to TEC and BPC components.

From the results of conventional DEA models, this study found that Group 1 was the highest in operational efficiency among all groups, which indicated that power producing companies focusing on one country/region is operating more efficiently in comparison to those that are doing business in different areas. The values of GMI showed that all four groups have average index higher than 1, thereby the operational efficiency of them has grown over the 10 years of the study period. It is noted that Group 1 and Group 4 had relatively large volatility and gap between extreme values. In particular, the major reason for the rapid increase of Group 1 in 2012 and 2013 is that TEC attained high level value, which means that companies transacting in one country/region largely improved in catch-up effects to the frontier. This is probably due to management efficiency that adopts single country/region business environment and institutional changes to cope with, avoiding management costs for various treatment of adaptations. Further, from the decomposition analysis of GMI, we found that TEC of four groups are more distinguishing than BPC. This indicates that companies' catch-up effects has improved significantly but with rather volatile way, compared with the total technological progress over time.

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References

Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39(10), 1261–1264. https://doi.org/10.1287/mnsc.39.10.1261

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9). https://doi.org/10.1287/mnsc.30.9.1078

Curtis, P. G., Hanias, M., Kourtis, E., & Kourtis, M. (2020). Data envelopment analysis (DEA) and financial ratios: A pro-stakeholders' view of performance measurement for sustainable value creation of the wind energy. *International Journal of Economics and Business Administration*, 8(2), 326–350. https://doi.org/10.35808/ijeba/465

Guaita-Pradas, I., & Blasco-Ruiz, A. (2020). Analyzing profitability and discount rates for solar PV Plants. A spanish case. *Sustainability (Switzerland)*, 12(8). https://doi.org/10.3390/SU12083157

Halkos, G. E., & Tzeremes, N. G. (2012). Analyzing the Greek renewable energy sector: A data envelopment analysis approach. *Renewable and Sustainable Energy Reviews*, 16(5), 2884–2893. https://doi.org/10.1016/j.rser.2012.02.003

Ibarloza, A., Heras-Saizarbitoria, I., Allur, E., & Larrea, A. (2018). Regulatory cuts and economic and financial performance of Spanish solar power companies: An empirical review. *Renewable and Sustainable Energy Reviews*, 92(May), 784–793. https://doi.org/10.1016/j.rser.2018.04.087

Kao, C. (2010). Malmquist productivity index based on common-weights DEA: The case of Taiwan forests after reorganization. *Omega*, 38(6), 484–491. https://doi.org/10.1016/j.omega.2009.12.005

Kuo, C. (2011). Cost efficiency estimations and the equity returns for the US public solar energy firms in 1990-2008. *IMA Journal of Management Mathematics*, 22(4), 307–321. https://doi.org/10.1093/imaman/dpq011

Luts, M.-K., Savolainen, J., & Collan, M. (2021). Profitability Determinants of Unlisted Renewable Energy Companies in Germany - A Longitudinal Analysis of Financial Accounts. *Sustainability*, 13(24).

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A., & Khoshnoudi, M. (2017). A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renewable and Sustainable Energy Reviews*, 70, 1298–1322. https://doi.org/10.1016/j.rser.2016.12.030

Mombini, E., Rostamy-Malkhalifeh, M., Saraj, M., Zahraei, M., & Tayebi Khorami, R. (2020). Global malmquist index for measuring the economic productivity changes. *Measurement and Control (United Kingdom)*, 53(7–8), 1278–1285. https://doi.org/10.1177/0020294020923096

Pastor, J. T., & Lovell, C. A. K. (2005). A global Malmquist productivity index. *Economics Letters*, 88(2), 266–271. https://doi.org/10.1016/j.econlet.2005.02.013

Paun, D. (2017). Sustainability and financial performance of companies in the energy sector in Romania. *Sustainability (Switzerland)*, 9(10). https://doi.org/10.3390/su9101722

Rastogi, R., Jaiswal, R., & Jaiswal, R. K. (2020). Renewable energy firm's performance analysis using machine learning approach. *Procedia Computer Science*, 175, 500–507. https://doi.org/10.1016/j.procs.2020.07.071

Schabek, T. (2020). The financial performance of sustainable power producers in emerging markets. *Renewable Energy*, 160, 1408–1419.

https://doi.org/10.1016/j.renene.2020.06.067

Tomczak, S. K. (2019). Comparison of the financial standing of companies generating electricity from renewable sources and fossil fuels: A new hybrid approach. *Energies*, 12(20). https://doi.org/10.3390/en12203856

Zhang, H., Zheng, Y., Ozturk, U. A., & Li, S. (2016). The impact of subsidies on overcapacity: A comparison of wind and solar energy companies in China. *Energy*, 94, 821–827. https://doi.org/10.1016/j.energy.2015.11.054

Zhang, H., Zheng, Y., Zhou, D., & Zhu, P. (2015). Which subsidy mode improves the financial performance of renewable energy firms? A panel data analysis of wind and solar energy companies between 2009 and 2014. *Sustainability (Switzerland)*, 7(12), 16548–16560. https://doi.org/10.3390/su71215831