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Original Research

Applying Stochastic Frontier Analysis to Measure the Operating Efficiency of Solar Energy Companies in China and Taiwan

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Abstract

Climate change and the depletion of fossil fuels are the biggest challenges that humanity faces today. Solar energy can be used to mitigate climate change and reduce the demand for fossil fuels. Therefore, governments in different countries have actively developed the solar energy industry as a renewable energy industry. Although China and Taiwan respectively occupy first and second place in the current global output of solar energy products, they face serious pressure in the international market. To measure the operating efficiency of solar energy companies in China and Taiwan, this study combines the Shephard distance function and stochastic frontier analysis incorporating environmental variables. The empirical results show that: (1) China has better labour efficiency, (2) Taiwan has better operating cost efficiency, (3) both regions have extremely poor expenditure efficiency on R&D and the R&D expenditure rate is low, (4) the larger a company's size, the higher the labour efficiency and cost efficiency, and (5) the prices of raw materials have a direct impact on operating costs. It is hoped that the results of this research can provide recommendations for and promote changes in the operating and management strategies of the solar energy industry, improving its operating efficiency.

Keywords: solar energy industry, efficiency measure, stochastic frontier analysis, climate change

Introduction

Since the industrial revolution of the 1750s, human economic activities have developed rapidly. The extensive burning of fossil fuels (such as raw coal, crude oil, and natural gas) has led to continued increases in the concentrations of greenhouse gases in the atmosphere – such as water vapor (H_2O), carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), ozone (O_3), chlorofluorocarbons (CFCs) and Hydro fluorocarbons (incl. HCFCs and HFCs), which all lead to climate change. Since the beginning of the industrial revolution we have produced a 40% increase in the atmospheric concentration of carbon dioxide (CO_2), the full record being from 340 ppm in 1980 to 409 ppm in early 2018 [1].

Fossil energy resources such as coal, oil and natural gas account for the largest proportion of energy worldwide, they also produce more environmental pollution than renewable energy [2]. The data of fossil fuel show that coal, oil and natural gas account for 85.9% of primary energy consumption. The

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International Energy Agency has predicted that global oil can be extracted for around 45 years, and coal can be extracted for round 230 years [3, 4]. Nuclear power used nuclear reactions to release nuclear energy. The issue of nuclear power plant disasters has been the topic of social debate since the first nuclear reactor was constructed in 1954 [5]. Nuclear power plant disasters may involve significant casualties and losses of life and property. Serious nuclear power plant disasters include Three Mile Island (1979), Chernobyl (1986), and Fukushima Daiichi (2011). Since Fukushima, people have doubted the safety of nuclear power plants, and many countries have closed or are planning to close their nuclear power plants. The safety of an energy source is another big concern for selecting an alternative. Therefore, many countries have recognized that the development of safe renewable energy sources is necessary for the environment as well as the economy [6].

As environmental awareness and the need to reduce air pollution have increased, renewable energy has become an important energy source in industrialized countries [2]. The mitigations of climate change, energy demands and energy related to global warming effects are the most important factors today. However, renewable energy is one of the alternative sources that have the capacity to reduce climate change and mitigate greenhouse gas emissions [7, 8]. Natural energy sources include sunlight, wind, rain, tides, waves, and geothermal heat. Renewable energy sources include solar energy, wind energy, hydroelectric power, geothermal energy, tidal energy, and wave energy [9]. Energy researchers and policy decision makers around the world are now utilizing renewable energy as a solution to this crisis, with a special focus on solar energy, as it is one of the most non-polluting, inexhaustible and the cleanest renewable energy source [7, 8, 10].

Renewable energy (excluding hydroelectric power) grew by 14.1% in 2016 – below the 10-year average, but the largest increment on record (53 mtoe). Wind energy provided more than half of renewable growth, while solar energy contributed almost a third despite accounting for only 18% of the total. Asia Pacific overtook Europe and Eurasia as the largest producing region of renewable energy. China overtook the US to be the largest single renewable energy producer [3]. Recently, the tremendous growth in the world solar industry is helping to pave the way to a cleaner, more renewable energy future. Over the past few years, the cost of a solar energy system has dropped significantly and has helped to give more families and business access to affordable clean energy [11].

Solar power is the conversion of energy from sunlight into electricity. Photovoltaic cells convert light into an electric current using the photovoltaic effect. Through a portfolio of research and development (R&D) efforts, the solar industry remains committed to leveraging a nation's abundant solar energy resources to drive research, manufacturing and market solutions to support widespread expansion of the solar market [11].

The International Energy Agency has projected that the solar photovoltaic and concentrated solar power would contribute about 16 and 11 percent, respectively, of worldwide electricity consumption, and solar power would be the world's largest source of electricity in 2050. Most solar system installations would be in China and India. As of 2016, the solar energy provided just 1% of total worldwide electricity production but was growing at 33% per annum. China is expected to overtake Europe as the largest producer of PV electricity soon after 2020, with its share regularly increasing from 18% of global generation by 2015 to 40% by 2030, and then slowly declining to 35% by 2050. From 2030 to 2050, the share of India and other Asian countries is expected to rise from 13% to 25%. By contrast, the United States' share is expected to remain at about 15% from 2020 on, and Europe's share to decrease constantly from 44% in 2015 to 4% in 2045 [12, 13].

The development of the solar energy industry in China and Taiwan began later than in the West, but has now surpassed it. At present, China and Taiwan enjoy first and second places respectively in the global output value of solar energy products, with China accounting for around 70%, Taiwan accounting for around 10%, and Japan, South Korea, and Germany making up the rest [14]. However, the West still holds many of the major patented technologies for solar energy. In contrast, China and Taiwan lack many core technologies, which is not conducive to price competition in the international market. Moreover, in recent years Western countries have imposed import tariffs on China and Taiwan, creating a crisis in solar energy industry chains.

Although China and Taiwan are two separate economies, in terms of technological development industries such as semiconductors, they are reliant on both each other and competitors. In the solar energy industry, both China and Taiwan face the problem of ownership of proprietary technologies by the West and the blocking of these technologies. In addition, the technology gap has led to increased costs. Both China and Taiwan are also facing internal and external risks in the international market, such as price competition, raw material costs, technological research and development (R&D), and company operating performance.

In summary, the solar energy industry in China and Taiwan is facing exposure to harsh internal and external environmental factors and risks. This study examines how to improve the operational effectiveness of the solar industry, exploring whether there are influencing factors that can be improved in the face of the impact of price competition and cost reduction in the market.

Recently, the topic of how to measure efficiency has drawn quite a bit of attention from researchers [15]. The concept of efficiency can be traced back to Farrell [16], who developed many ideas underlying data envelopment analysis (DEA) and stochastic frontier analysis (SFA) [17]. At present, the new energy industry and the solar photovoltaic industry used data envelopment analysis and stochastic frontier analysis to measure energy use efficiency. Wu et al. [18] applied DEA and Malmquist indices to examine the efficiency of energy utilization in thirty provinces in China. The results showed that the average efficiency of energy utilization of enterprises in the Eastern region during the period from 2006 to 2009 was better than that in the Central region. Chen and Shihong [19] applied DEA to explore the efficiency and benefits of China's solar energy industry. The results showed that the overall financing efficiency and technical efficiency are the best in the Eastern region. In addition, the Western region has the best installations of solar energy plants but also the lowest installation rates.

Tu et al. [20] used DEA to create a weight-restricted dynamic energy efficiency indicator, and discusses issues concerning the energy decoupling rate and decarbonization. This study utilized members in the Group of Seven (G7, include Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) and BRICS (Brazil, China, India, Russia, and South Africa) for the experimental observations. The findings are: (1) BRICS has more room for improvement to achieve the standard ratio of the energy decoupling rate than the G7; (2) the G7 and BRICS do not converge to decarbonization; and (3) BRICS exhibits more rapid improvement on energy efficiency than the G7. Lee and Tong [2] accurately predicted whether transfer efficiency of a photovoltaic power generation system is high or low using a novel hybrid model that combines rough set theory, data envelopment analysis, and genetic programming. Chueh and Jheng [21] used two-stage data envelopment analysis to evaluate the operating efficiency and profitability of Taiwan's listed solar cell manufacturers. This study's primary contribution is in constructing a performance evaluation model for the solar cell industry to assist relevant manufacturers in formulating operational strategies. Lee et al. [22] proposed a performance evaluation model by integrating the analytic hierarchy process and data envelopment analysis to assess the current business performance of PV companies. Stern [23] measured energy efficiency by applying SFA to 85 countries and examining the determinants of inefficiency. Herrala and Goel [24] studied global carbon dioxide (CO2) efficiency for more than 170 countries. Honma and Hu [25] used the SFA model to estimate the total-factor energy efficiency scores for 47 regions across Japan during the years 1996-2008. Lee et al. [26] used DEA to assess suitable locations for renewable energy plants. They used temperature and wind speed as inputs, and sunshine hours and elevation as output data to select 15 townships in Taiwan as the best places for establishing photovoltaic plants. Liu et al. [4] used DEA to construct a comprehensive evaluation model for the efficiency of photovoltaic power generation in China between 2005 and 2015, exploring the input and output efficiency of installed capacity from the perspective of resource, development, and utilization efficiencies.

In recent years, performance evaluation methods have been widely used and valued to measure the efficiency of various industries. The main reason is that decision makers in both public and private institutions want to understand whether their organization is efficiently utilizing resources. A performance assessment can serve as a reference for decision-making. In addition, indicators of efficiency of for-profit organizations are usually based on objective and quantifiable assessment methods using quantifiable financial inputs and outputs such as operating costs, incomes, and salaries. In terms of research methods for measuring efficiency, a variety of objective assessment methods have been developed, including regression analysis, multi-criteria decision analysis (MCDA), and frontier analysis. Frontier analysis often uses DEA or SFA for analysis. DEA is used by most researchers because it is simple and there is no need to construct a function. This method can be used to compare the relative efficiencies of different research subjects, but it cannot account for external environmental variables. Meanwhile, the SFA method has been widely used in many areas of performance evaluation research, but fewer studies have used this method. Nevertheless, SFA can explore the absolute efficiency and interrelationships between all of the input influencing factors and efficiencies, and can also include external environmental variables, so the effects of efficiency factors and environmental variables can be analyzed simultaneously.

This study collects publically available financial report data from listed solar energy companies in China and Taiwan. It uses the SFA method to construct an efficiency model for the solar industry in China and Taiwan in order to explore the relationships between factors affecting industry and efficiency, incorporates environmental variables to explore their impact on efficiency, and proposes future business strategies and suggestions for improvement.

Material and Methods

Methodology

To include statistical noises in efficiency analysis, Zhou et al. [27] presented a parametric frontier approach to measuring efficiency performance at an economy-wide level. The proposed approach used the Shephard distance function to define an efficiency index and applied the stochastic frontier analysis model to estimate the efficiency index. Honma and Hu [25] extended the cross-sectional stochastic frontier analysis proposed by Zhou et al. [27] to panel data models and add environmental variables.

This study assumes that the production function is a Cobb–Douglas function and estimates the disaggregate input efficiency for the three inputs and one output. First, the combination of input and output T is defined. Productivity can be described as follows [25, 27, 28]:

$$T = \{(X1, X2, X3, Y) : (X1, X2, X3)\ can\ produce\ Y\} \quad (1)$$

To calculate the technical efficiency of *X1*, the Shephard distance function of *X1* is defined as [25, 27, 28]:

$$D_{X1}(X1, X2, X3, Y) = sup\{\alpha : (x1/\alpha, X2, X3, Y) \in T\} \quad (2)$$

Since $D_{X1}(X1, X2, X3, Y) \geq 1$ the technical efficiency of *X1* is equal to $1/D_{X1}(X1, X2, X3, Y)$.

SFA is used to calculate $D_{X1}(X1, X2, X3, Y)$. Suppose there are n decision marking units (DMU) in period t. Thus, the combination of input and output for the i^{th} DMU is $(X1_{it}, X2_{it}, X3_{it}, Y_{it})$. Therefore, the Shephard distance function of *X1* can be expressed as $D_{X1}(X1_{it}, X2_{it}, X3_{it}, Y_{it})$. After obtaining the translog of the Cobb-Douglas production function, Equation (3) is obtained [25, 27, 28]:

$$\ln D_{X1}(X1_{it}, X2_{it}, X3_{it}, Y_{it}) = \beta_0 + \beta_{X1}\ln X1_{it} + \beta_{X2}\ln X2_{it} + \beta_{X3}\ln X3_{it} + \beta_Y \ln Y_{it} + V_{it} \quad (3)$$

…where $D_{X1}(\cdot)$ is the distance function and V_{it} is the statistical noise, which is assumed to be normally distributed. Because the distance function is homogeneous to one degree in the input, the above equation can be rearranged as [25, 27, 28]:

$$\ln D_{X1}(X1_{it}, X2_{it}, X3_{it}, Y_{it}) = \ln X1_{it} + \beta_0 + \beta_{X1}\ln 1 + \beta_{X2}\ln X2_{it} + \beta_{X3}\ln X3_{it} + \beta_Y \ln Y_{it} + v_{it} \quad (4)$$

…which can be rewritten as:

$$-\ln X1_{it} = \beta_0 + \beta_{X1}\ln 1 + \beta_{X2}\ln X2_{it} + \beta_{X3}\ln X3_{it} + \beta_Y \ln Y_{it} + v_{it} - \ln D_{X1}(X1_{it}, X2_{it}, X3_{it}, Y_{it}) \quad (5)$$

Thus,

$$\ln(1/X1_{it}) = \beta_0 + \beta_{X2}\ln X2_{it} + \beta_{X3}\ln X3_{it} + \beta_Y \ln Y_{it} + v_{it} - u_{it} \quad (6)$$

Following Honma and Hu [25], where u_{it} is the inefficiency term, which follows a non-negative distribution, and $v_{it} - u_{it}$ is the error component term of a stochastic production frontier. Equation (6) is consistent with the panel data stochastic frontier model proposed by Battese and Coelli [29].

Data and Empirical Model

Samples and Data Sources

This study collected financial data over a period of eight years from listed solar energy companies in China and Taiwan. After removing companies whose main products were not solar energy products or who had incomplete data for the sample period, we obtained 32 solar energy companies in China and 16 solar energy companies in Taiwan, for a total sample of 48 companies and 384 data points. This study selected the number of employees (labour), operating costs, and R&D costs as the three inputs and the gross output as the output. The sample data came from annual company financial reports in the databases of the Taiwan Economic Journal (TEJ). Since the sample period is eight years, we used the 2009 price index as the base period, applying deflators. In addition, because the currencies of China and Taiwan are different, both currencies were converted into US dollars using the average annual exchange rate of each currency.

Variables

The solar energy industry is a labour-intensive, material-intensive, and capital-intensive industry [30]. Urban et al. [31] believed that the solar energy industry is also a patent-intensive industry. Coad and Rao [32] argued that as the gross output and number of employees of a company increases, the R&D expenditure also increases.

Based on the characteristics of the solar energy industry, this study selected three input items – labour (L), operating costs (TC), and R&D expenditures (R) – as the input items, and gross output (net sales, Q) as the output item. The distance function models for each of the three inputs were constructed separately, and SFA was used to estimate the input efficiency of each item separately. This study also included environmental variables, including capital amount (CA) and raw

Table 1. Descriptive statistics of variables.

Variables	Unit	Samples	Mean	Std.	Min.	Max.
Total cost	USD$1000	384	390,341	651,932	322	5,074,188
Labour	person	384	3,095	4,341	34	18,098
Net sales	USD$1000	384	328,785	534,845	2,153	4,168,540
R&D expenditure	USD$1000	384	10,807	23,107	23	211,191
Capital stock	USD$1000	384	112,866	100,193	6,032	683,713
Raw material costs	USD$1000	384	21,166	28,205	19	235,693

material cost (RM). It also added a virtual variable (AREA) that distinguishes between China and Taiwan, where China is labelled as 1, and Taiwan is labelled as 0. The statistics of the variables in this study are listed in Table 1.

Empirical Model

This study combines the work of Zhou et al. [27] and Battese and Coelli [29], and also refers to the work of Honma and Hu [25] in order to construct a disaggregated input efficiency function model, as shown in Equation (6).

Labour input efficiency:

$$\ln(1/L_{it}) = \beta_0 + \beta_{TC}\ln TC_{it} + \beta_R \ln R_{it} + \beta_Y \ln Q_{it} + v_{it} - u_{it} \tag{7}$$

Operating cost input efficiency:

$$\ln(1/TC_{it}) = \beta_0 + \beta_L \ln L_{it} + \beta_R \ln R_{it} + \beta_Y \ln Q_{it} + v_{it} - u_{it} \tag{8}$$

R&D investment efficiency:

$$\ln(1/R_{it}) = \beta_0 + \beta_L \ln L_{it} + \beta_{TC}\ln TC_{it} + \beta_Y \ln Q_{it} + v_{it} - u_{it} \tag{9}$$

This study also includes environmental variables in order to analyse the impact of environmental variables on u_{it}.

$$u_{it} = \delta_0 + \delta_1 lnCA_{jt} + \delta_2 lnRM_{jt} + \delta_3 AREA + \varepsilon_{it} \tag{10}$$

In this study, the estimating equations for the input efficiencies of each item are used to estimate the input efficiencies of each company, in order to analyse the impact of environmental variables on input efficiency. The efficiency analysis for the number of employees uses Equations (7) and (10) to calculate the labour input efficiency of each company and analyse the impact of environmental variables on labour input efficiency. Second, we used Equations (8) and (10) to calculate the operating cost input efficiency and analyse the impact of environmental variables on it. Finally, we used Equations (9) and (10) to calculate the R&D input efficiency of each company in order to analyse the impact of environmental variables on R&D input efficiency. The free software "Frontier Version 4.1" can be used to estimate the equations, which was kindly provided by Professor Coelli [33].

Results and Discussion

Analysis of Labour Efficiency

Table 2 shows the result of stochastic frontier analysis of labour efficiency. Fig. 1 shows the average labour efficiency values for China and Taiwan in 2009-2016, which were 0.93 in China and 0.28 in Taiwan.

From Fig. 1 and the annual average values, we find polarised differences in the labour efficiency values between China and Taiwan. The results show that China has better labour efficiency and that Taiwan's labour efficiency is far lower than that of China, so there is still considerable room for improvement in Taiwan's labour force. In addition, the results in Table 2 show there is a significant negative correlation between operating costs and labour efficiency; R&D spending has a strongly significant negative correlation with labour efficiency. The results for operating costs show that if a company wants to increase its production

Table 2. Estimates of the translog of labour force by frontier function.

Table 2-1. Parameter estimates of the translog labour force frontier function				
Variable description	Coefficient	Estimate	Standard error	t-ratio
Constant	β_0	0.24802	0.49616	0.49987
InTC_{it}	β_1	-0.34525	0.14278	-2.41807*
InR_{it}	β_2	-0.11968	0.02667	-4.48693**
InQ_{it}	β_3	-0.23833	0.14365	-1.65908*
Table 2-2. Estimates of the labour force inefficiency				
Constant	δ_0	4.44850	0.59508	7.47547**
$lnCA_{jt}$	δ_1	-0.32571	0.05686	-5.72817**
lnM_{jt}	δ_2	0.06815	0.04996	1.36422
AREA	δ_3	-1.66489	0.13980	-11.90924**
log likelihood function = -324.56913				

Note: **, and * represent significance at the 1%, and 5% levels, respectively.

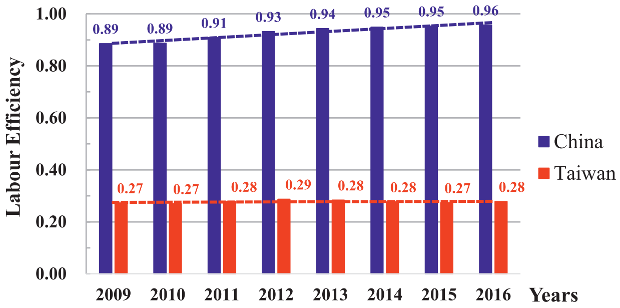

Fig. 1. The average labor force factor efficiency values for China and Taiwan in 2009-2016.

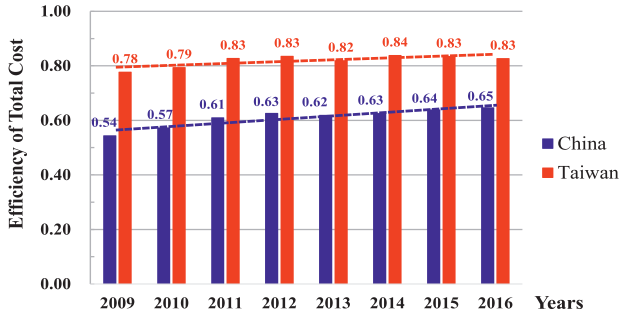

Fig. 2. Average total cost factor efficiency values for China and Taiwan in 2009-2016.

it needs to hire more employees. This also represents a positive relationship between cost expenditure and direct labour costs. In addition, high-tech companies must constantly research new products in order to increase market competitiveness and expand company size so as to avoid market obsolescence. This shows that increases in the number of employees and company size will be accompanied by increased R&D spending. The results of this study are consistent with the findings of Coad and Rao [32]. When companies increase operating income and the number of employees, they will also increase R&D expenditure.

With regard to the impact of environmental variables, there is a strongly significant negative correlation between the amount of capital and labour efficiency. The results of the research show that the larger the scale of the company, the better the labour efficiency. This may be because larger companies have better management capabilities, which will produce better labour performance. This result is consistent with the research results of Eling and Luhnen [15], Eken and Kale [34], and Dzeng and Wu [35]. However, they also reported that there is a limit to the scale efficiency of a company. It is not efficient to expand the scale of the company indefinitely, and this may actually become counterproductive.

In addition, there is a strongly significant negative correlation between the dummy variable for labour efficiency and area. In other words, there are strongly significant differences between the labour forces in China and Taiwan. Although China and Taiwan have the same culture and race, after 50-60 years of separation, there are extremely large differences in many beliefs. First, labour costs in China are lower than in Taiwan. Although they have begun to close in recent years, there are still big differences in the salaries of operations workers. Second, through employee training systems and standardised operating procedures, the high-tech industry in China is able to apply strict internal control, establish workplace concepts and operating techniques, increase team spirit, and achieve management objectives. However, at present, China's low salaries, long working hours, and centralised management methods may only deliver better labour results in the short term. As time progresses, differences in how different generations view work, the era of high productivity, and low wages

Table 3. Estimates of the translog of total cost by frontier function.

Table 3-1. Parameter estimates of the translog total cost frontier function				
Variable description	Coefficient	Estimate	Standard error	t-ratio
Constant	β_0	-2.12371	0.16968	-12.51570**
InL_{it}	β_1	-0.04992	0.01651	-3.02393**
InR_{it}	β_2	-0.00170	0.00913	-0.18598
InQ_{it}	β_3	-0.81482	0.01685	-48.34704**
Table 3-2. Estimates of total cost inefficiency				
Constant	δ_0	2.39706	0.21107	11.35680**
$lnCA_{jt}$	δ_1	-0.14778	0.01515	-9.75546**
lnM_{jt}	δ_2	-0.06413	0.01341	-4.78245**
AREA	δ_3	0.36971	0.04337	8.52399**
log likelihood function = 117.86176				

Note: **, and * represent significance at the 1%, and 5% levels, respectively.

Table 4. Estimates of the translog of R&D by frontier function.

Table 4-1. Parameter estimates of the translog R&D frontier function				
Variable description	Coefficient	Estimate	Standard error	t-ratio
Constant	β_0	-1.24600	0.42359	-2.94152**
InL_{it}	β_1	-0.55280	0.05480	-10.08773**
InTC_{it}	β_2	-0.02051	0.16909	-0.12130
InQ_{it}	β_3	-0.29453	0.15553	-1.89372
Table 4-2. Estimates of R&D inefficiency				
Constant	δ_0	-54.27044	31.23735	-1.73736
$lnCA_{jt}$	δ_1	1.05549	0.68800	1.53415
lnM_{jt}	δ_2	1.31433	0.97271	1.35121
AREA	δ_3	4.80358	2.71121	1.77175
log likelihood function = -516.83652				

Note: **, and * represent significance at the 1%, and 5% levels, respectively.

will quickly disappear. For this area, policy makers and managers should actively seek new strategies to respond and adapt to future changes.

Operating Costs Input Efficiency Analysis

Table 3 shows the results of the stochastic frontier analysis of operating cost efficiency. Fig. 2 shows the average operating cost efficiencies for China and Taiwan in 2009-2016, which were 0.61 in China and 0.82 in Taiwan.

As shown in Fig. 2, Taiwan's operating cost efficiency is better than China's, but there is still room for improvement in both areas. In addition, as shown in Table 3, the number of employees and gross output have a strong negative correlation with operating cost efficiency. The amount of capital in environmental variables also has a strong negative correlation with operating cost efficiency. These three items all show that larger companies have better cost efficiency. This may be because larger companies can use more resources and are more competitive in the market.

With regard to the impact of environmental variables, raw materials also have a strong negative correlation with operating cost efficiency. This shows that the prices of raw materials have a direct impact on operating costs. Silicon is the most important basic raw material for the semiconductor and solar cell industries. In other words, the market prices of silicon raw materials will be one of the main factors that directly affect the profitability of a solar company. In addition, the area dummy variable has a strongly significant positive correlation with operating cost efficiency. This shows that there are indeed differences between the operating cost efficiencies of China and Taiwan. The estimates show that the performance of Taiwan is 1.3 times greater than that of China.

R&D Cost Input Efficiency Analysis

Table 4 shows the results of the stochastic frontier analysis for R&D expenditures. Figure 3 shows the average efficiencies for R&D expenditures for China and Taiwan in 2009-2016, which were 0.50 in China and 0.49 in Taiwan.

As Table 4 shows, R&D expenditure inefficiency has a strongly significant negative correlation with the labour force. This estimate is the same as the result of the previous labour efficiency analysis. As shown in Fig. 3 and by the input efficiency values, the R&D expenditures in both China and Taiwan are inefficient and have considerable room for improvement. In addition, the present study used statistics from the financial statements of solar companies in China and Taiwan, which showed that the rate of expenditure on R&D in both areas is low (R&D expenditure rate = (operating expenses on R&D) / (net operating income) × 100%). During the sample period from 2009 to 2016, the annual average for the two areas was only

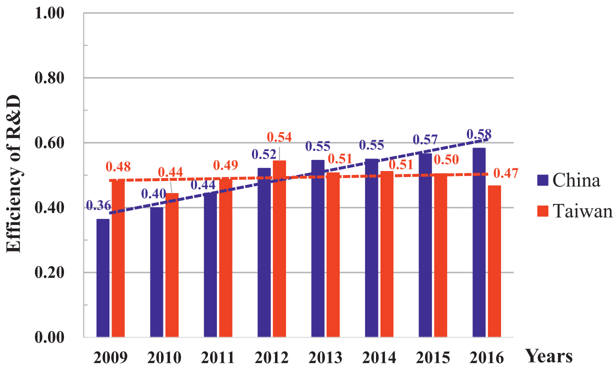

Fig. 3. Average R&D factor efficiency values for China and Taiwan in 2009-2016.

approximately 5%. The results of this study are in line with the findings of Wang et al. [36] that the R&D efficiency of solar energy companies is not good.

In addition, Ferroni and Hopkirk [30] analysed the influence of the development of patent technologies on the market value of South Korean renewable energy listed companies over 35 years from 1980 to 2014. Their research showed that patented technologies have a very significant impact on the market values of companies. In other words, patented technologies can increase the economic value of renewable energy companies.

At present, different technologies in the solar energy industry have the issue of high costs. The most important of these are patented technologies for solar energy products that have been blocked by Western countries. These technological gaps lead to increases in production costs. If there is insufficient investment in R&D in the solar energy industry in China and Taiwan, then a lack of core technologies, market price competition, technological development, and financial arrangements will all affect the development of the solar industry. If China or Taiwan fail to actively increase R&D expenditures, improve technology, and increase product differentiation to expand their economic scales, then they will have difficulty coping with the pressure of global economic competition and may face elimination from the market.

Conclusions

Since the industrial revolution of the 1750s, human economic activities have developed rapidly. Fossil energy resources such as coal, oil and natural gas account for the largest proportion of energy worldwide, and they also produce more environmental pollution (such as CO_2, CH_4, N_2O and O_3). The extensive burning of fossil fuels in the atmosphere leads to climate change – which along with the depletion of fossil fuels are the biggest challenges that humanity faces today. Energy researchers and policy decision makers around the world are now placing special focus on solar energy, as it is one of the most non-polluting, inexhaustible and cleanest renewable energy sources.

Although China and Taiwan respectively occupy first and second place in the current global output of solar energy products, they face serious pressure in the international market. In order to measure the operating efficiency of solar energy companies in China and Taiwan, this study used the Shephard distance function to define the efficiency of different items in solar energy companies. The study applied stochastic frontier analysis and incorporated environmental variables to measure the operating efficiencies of solar energy companies. The study sample contained 384 financial data points of 48 solar energy companies in China and Taiwan over a period of eight years (2009–2016). The main empirical findings are: (1) China has better labour efficiency, (2) Taiwan has better operating cost efficiency, (3) both regions have extremely poor expenditure efficiency on research and development (R&D) and the R&D expenditure rate is low (approximately 5% of net operating income), (4) the larger a company's size, the higher the labour force efficiency and cost efficiency and (5) the prices of raw materials have a direct impact on operating costs.

Based on the results of this study, we suggest that the solar industry adopt the following strategies for improvement: (1) adopt automated production to reduce labour demand and costs in order to increase production efficiency; (2) appropriately expand the economic scale of companies to improve labour efficiency and cost efficiency; (3) increase R&D costs to develop new core patent technologies, improve technology, increase product differentiation, reduce product costs, and face international market competition; and (4) search for alternative raw materials in order to reduce the risk of cost increases caused by fluctuations in the price of raw materials.

It is hoped that the results of this research will gain the attention of solar energy companies in China and Taiwan and help them to decrease their operating costs and improve their management strategies. The results and recommendations of this research can be applied to the solar energy industry in other countries.

Data Availability Statement

The sample data came from annual company financial reports in the databases of the Taiwan Economic Journal (TEJ). All data generated or used during the study are available from the corresponding author by request.

– The data of 32 solar energy companies in China and 16 solar energy companies in Taiwan, for a total sample of 48 companies and 384 data points.
– Models generated or used during the study appear in the submitted article.

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Conflict of Interest

The authors declare no conflict of interest.

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