APPLYING DATA ENVELOPMENT ANALYSIS TO EVALUATION OF TAIWANESE SOLAR CELL INDUSTRY OPERATIONAL PERFORMANCE

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ABSTRACT

In the Taiwanese solar power industry, the upstream industry's lack of silicon raw materials and the downstream's underdeveloped systematic manufacturing status have led industrial development to continue concentrating on cell and module research and development manufacturing and production. Taiwan's solar power industry has developed midstream cell manufacturers holding a share of the global market. The research period for this study was between 2010 and 2011. This study constructed a performance evaluation model by using data envelopment analysis for the solar cell industry to assist relevant manufacturers in the Taiwanese solar power industry in formulating operational strategies; guidelines on future development in the industry have been recommended.

KEYWORDS

Data Envelopment Analysis, Performance Evaluation, Solar Cell Industry

1. INTRODUCTION

Taiwan's solar power industry has developed midstream cell manufacturers competing in the global market. Therefore, examining the operating performance of Taiwanese solar cell manufacturers is vital for the international competitiveness of Taiwanese manufacturing. Similar to the semiconductor industry, solar cell production and manufacturing is based on rapid investment and superior high-technology manufacturing management. Taiwan has an excellent industrial presence in the global market for computers, information, panel displays, and CD and disk industries, and superior global logistic capabilities to market and sell worldwide. Taiwanese investment in solar cell research and development has progressed from initial non-silicon solar cell research, development, and production to the production and development of silicon solar cells [5].

Encouraged by high global demand, investment into Taiwan's solar cell industry has increased, and existing crystalline silicon solar cell factories have continued to expand production capabilities. Although some manufacturers face material shortages and rely on supply contracts from large international companies, many new entrants into the industry, investing in polysilicon materials, thin-film cells, and module mass production, are optimistic regarding the industry's prospects and development.

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This study examined the operational performance of midstream manufacturers in Taiwan's solar cell industry by using data envelopment analysis (DEA), researching the solar cell industry's development and market competitiveness, and analyzing unique industry features. Through performance evaluations and empirical analysis, the industry's benchmark companies examined the factors causing inefficiencies to assist operational performance improvements among existing solar cell manufacturers and to provide a reference for future manufacturers interested in entering this industry.

2. PRELIMINARIES

Some basic concepts involved in DEA are introduced in this section.

DEA [1, 2, 3, 4, 6] is a method used to estimate production efficiency using a nonparametric analysis technique. This method is able to consider multiple variables simultaneously.

Based on Farrell's (1962) envelope theorem and deterministic nonparametric method [4], Charnes, Cooper, and Rhodes (hereafter referred to as CCR) demonstrated the approach of efficiency estimation DEA in 1978; the units that are estimated are called decision making units (DMU). The purpose of the envelope theorem is to connect inputs and outputs of DMUs with a curved line; this line is called the Efficiency Frontier Curve (EFC). When outputs fall on the efficiency frontier curve, the combinations of inputs and outputs are believed to be efficient; when outputs do not fall on the curve, the input-output combinations are inefficient.

The deterministic nonparametric method requires no assumptions of particular production functions. By examining DMU efficiency, improvements can be made.

DEA has three major models [1, 2, 3, 4, 6]: (1) The technical efficiency (TE) model as demonstrated by CCR, is used to analyze the technical efficiency of each DMU; (2) The pure technical efficiency (PTE) model as established by Banker, Charnes, and Cooper (hereafter referred to as BCC), is used to analyze the pure technical and scale efficiency (SE) of each DMU; and (3) The cost efficiency (CE) model, verified by Aly, Grabowski, Pasurka, and Rangan, is used to measure the cost and allocative efficiency (AE) of each DMU.

Building on the concept of Pareto optimality, the CCR model of DEA is used to measure efficiency frontiers with a linear programming model. In the analysis of the production theory, production functions mathematically represent the processes of converting inputs into outputs in relation to particular techniques. In a CCR model, the production frontier possibility set is built on DMUs—data of estimated units. A standard production frontier has an efficiency score of 1. When the input-output combination of a DMU falls on the frontier, the DMU is considered an efficient unit, or a Pareto optimum unit. This DMU then becomes the benchmark for comparing other DMUs. The input-output combinations of other DMUs falling within the frontier imply that the DMUs are inefficient units. The CCR model can be divided into two sub-models: the input orientation model and the output orientation model. In an input orientation model, the inefficient values range between 0 and 1. In an output orientation model, the inefficient values range between 1 and ∞. The purpose of dividing inefficient units by Pareto optimum units is to calculate the efficiency value.

The term Pareto optimal refers to a situation where allocating resources to compose any single unit without degrading other units is impossible. Conversely, non-Pareto optimal is a situation where allocating resources improves a certain unit without degrading other units. Analyzing the CCR model shows that a standard production frontier with an efficiency score of 1 can be constructed. A DMU falling on the production frontier is considered Pareto optimal and is a benchmark for comparing other DMUs; DMUs with efficiency scores of less than 1 are considered non-Pareto optimal. In DEA, efficient units are the standard of comparison of other DMUs. Therefore, the comparison results are relatively efficient, but not absolute.

A CCR model is used primarily to analyze the TE of each DMU; fractional linear programming can be applied to estimate the TE. Y_{jn} represents the n th output of the j th DMU, and X_{jm} represents the m th input of the j th DMU. Assuming that every DMU uses M inputs to generate N outputs, the technical efficiency TE_j of the j th DMU becomes the solution to the fractional linear programming problem.

$$Max \quad TE_j = \sum_{n=1}^{N} U_n Y_{jn} \Big/ \sum_{m=1}^{M} V_m X_{jm} \; ; \tag{1}$$

$$subject\ to \quad \sum_{n=1}^{N} U_n Y_{in} \Big/ \sum_{m=1}^{M} V_m X_{im} \le 1 \, , \; i = 1 \cdots R \; ; \tag{2}$$

where $U_n, V_m \ge 0$; $m = 1 \cdots M$; $n = 1 \cdots N$.

U_n and V_m are the virtual multipliers of the n th output and the m th input, respectively. The previous fractional linear programming equation should then be turned into a calculable linear programming equation to provide a solution.

$$Max \quad TE_j = \sum_{n=1}^{N} U_n Y_{jn} ; \tag{3}$$

$$subject\ to \quad \sum_{n=1}^{N} U_n Y_{in} - \sum_{m=1}^{M} V_m X_{im} \le 0 \; ; \tag{4}$$

$$\sum_{m=1}^{M} V_m X_{im} = 1 \; ; \tag{5}$$

where $U_n, V_m \ge 0$; $m = 1 \cdots M$; $n = 1 \cdots N$; $i = 1 \cdots R$.

Because the number of constraints is greater than the number of variables in the preceding solution, the dual proposition obtained from the original ratio is transformed into an envelopment form, as shown below.

$$Min \quad E_r = \phi - \varepsilon \sum_{m=1}^{M} S_m^- - \varepsilon \sum_{n=1}^{N} S_n^+ \; ; \tag{6}$$

$$subject\ to \quad \phi \cdot X_{jm} - \sum_{n=1}^{N} X_{im} - S_m^- = 0\ ; \tag{7}$$

$$Y_{jn} = \sum_{n=1}^{N} Y_{in} \cdot \lambda_i - S_n^+\ ; \tag{8}$$

where $\lambda_i,\ S_m^-,\ S_n^+ \geq 0,\ for\ m = 1 \cdots M\ ; n = 1 \cdots N\ ; i = 1 \cdots R$.

S_m^- and S_n^+ are the slack variables of the m th input and the n th output, and λ_i is the weight of the i th DMU. When the input and output are known, DEA finds the most beneficial virtual multiplier from the possible solution sets comprising individual DMUs, to maximize DMU efficiency. The model can also estimate the TE of each DMU.

The CCR model's hypothesis of return to scale is constant. When the hypothesis is not supported, estimating the PTE is possible. SE can also be generated from TE and PTE; TE is the result of multiplying PTE by SE. BCC demonstrated this efficiency model.

The BCC model is an extension of the CCR model, which requires production techniques to satisfy convexity assumptions and have changeable scales. With these requirements, the estimated TE is guaranteed to be pure (the effect of avoiding scale efficiency changes). PTE is obtained using the following formula:

$$Min \quad PTE_j = \theta - \varepsilon \sum_{m=1}^{M} S_{jm}^- - \varepsilon \sum_{n=1}^{N} S_{jn}^+\ ; \tag{9}$$

$$subject\ to \quad \sum_{i=1}^{R} \lambda_i \cdot X_{im} - \theta \cdot X_{jm} + S_{jm}^- = 0\ ; \tag{10}$$

$$\sum_{i=1}^{R} \lambda_i \cdot Y_{in} - S_{jn}^+ = Y_{jn}\ ; \tag{11}$$

$$\sum_{i=1}^{R} \lambda_i = 1\ ; \tag{12}$$

where $\lambda_i,\ S_{jm}^-,\ S_{jn}^+ \geq 0$.

The TE (obtained from the CCR model) divided by the PTE (obtained from the BCC model) equals the SE of a particular DMU.

The efficiency value obtained from the BCC model has four implications. First, using the mathematical relationship among TE, PTE, and SE, where PTE multiplied by SE equals TE is a possibility, and then dividing the TE results in SE. Second, by comparing data of SE and of PTE, several technical problems can be determined, such as the combination quantity of production factors causing the inefficiency of the analyzed unit. Third, if the PTE of inefficient DMUs is less than their SE, these DMUs must adjust their scales of production to improve their TE. Fourth, when the PTE is less than the SE, it indicates that the cause of inefficiency is a combination of factors; for instance, too many input factors are being used or insufficient outputs are being produced. Efficiency must be improved, and modifications should be applied accordingly.

Building on the CCR model, the CE model, in addition to either the data of factor input costs per unit or those of product price per unit, is able to measure CE.

The formula for calculating CE is as follows:

$$Min \quad CE_j = \sum_{m=1}^{M} C_{jm} \cdot X_{jm} - \sum_{n=1}^{N} \lambda_i \cdot X_{im} + X_{jm} + W_{jm} \; ; \tag{13}$$

$$subject\ to \quad \sum_{i=1}^{R} \lambda_i \cdot Y_m - W_{jn}^{+} = Y_{jn} \; ; \tag{14}$$

$$\sum_{i=1}^{R} \lambda_i = 1 \; ; \tag{15}$$

where $\lambda_i \geq 0$.

CE divided by TE obtained from the CCR model equals the allocative efficiency (AE) of a DMU. Additionally, to obtain price efficiency, the price data can replace the cost data used when obtaining CE.

3. METHODOLOGY

This study used a two-stage input-oriented BCC model to analyze the operational efficiency and profitability of the Taiwanese solar power industry between 2010 and 2011. The research procedures are described as follows:

Step 1: Select DMUs

The Taiwanese solar cell industry is an emerging industry, with young companies. This study considered the differences in specifications between listed and unlisted companies and chose to include only listed companies. After consulting the scope of the proportional production capacity of each solar cell factory in Taiwan in 2011, eight manufacturers of an appropriate scale were selected: Phoenix Silicon, Gintech Energy, E-Ton, Neo Solar Power, Motech, Tainergy Tech, Big Sun, and DelSolar. The financial data used for each variable calculation were obtained from the Taiwan Economic Journal Co., Ltd (TEJ) database; the research period was between 2010 and 2011.

Step 2: Determine variables

This study reviewed prior research on the solar power industry to select the input and output variables. Five input and output variables were selected for the first stage of performance evaluation: personnel number, operating expenses, fixed assets, total assets, and net operating revenue. Three input and output variables were selected for the second stage: net operation revenue, gross profit, and total shareholders’ equity.

Step 3: Construct a two-stage performance evaluation model

Whereas the single-stage model traditionally constructed by DEA can simultaneously process multiple input and output factors to find a DMU's overall efficiency value, it ignores stage efficiency in the industry's production process. The majority of one-stage DEA examine the operational ability, market ability, or profitability individually; these different factors, to examine efficiency and efficacy in the two-stage DEA, are rarely combined. The two-stage DEA concept, proposed by Seiford and Zhu (1999) [7], divides the production process into two stages according to the actual order and sequence of production; the product of the first stage is the input of the second stage. This method conforms to companies' actual management and operations processes, regardless of the number of stages, and reflects the efficiency of different stages better than the single-stage method. Therefore, this study based its performance evaluations on a two-stage input-oriented BCC model.

Step 4: Analyze results

The results from the two-stage performance evaluation of Taiwanese solar cell manufacturers from 2010 to 2011, using the data from the input and output variables, are outlined in the table below.

Table 3: The results of the first-stage performance evaluation.

DMU	Score	Rank
Gintech Energy 2010	1	1
Big Sun 2010	1	1
DelSolar 2010	1	1
Motech 2010	1	1
Phoenix Silicon 2010	0.912	5
Phoenix Silicon 2011	0.910	6
Tainergy Tech 2010	0.910	7
Neo Solar Power 2011	0.873	8
Big Sun 2011	0.871	9
Neo Solar Power 2010	0.851	10
E-Ton 2010	0.851	11
Gintech Energy 2011	0.791	12
Motech 2011	0.734	13
Tainergy Tech 2011	0.703	14
DelSolar 2011	0.556	15
E-Ton 2011	0.513	16

Table 4: The results of the second-stage performance evaluation.

DMU	Score	Rank
Tainergy Tech 2010	1	1
Motech 2010	1	1
Motech 2011	1	1
Neo Solar Power 2010	0.984	4
Gintech Energy 2010	0.961	5
Phoenix Silicon 2010	0.941	6
Gintech Energy 2011	0.818	7
Neo Solar Power 2011	0.817	8
Big Sun 2010	0.760	9
DelSolar 2010	0.709	10
E-Ton 2011	0.552	11
Tainergy Tech 2011	0.490	12
E-Ton 2010	0.448	13
Big Sun 2011	0.443	14
DelSolar 2011	0.351	15
Phoenix Silicon 2011	0.295	16

The table shows companies operating efficiently in 2010 in the first stage, which included Gintech Energy, Big Sun, DelSolar, and Motech. Companies with an efficient profitability during the second stage of 2010 included 2010, and Motech in 2010 and 2011.

4. CONCLUSION

Performance evaluation is a topic that has been explored by domestic industries in recent years. Scholars have increasingly presented research findings on the solar power industry. This study used a two-stage input-oriented BBC model to analyze the operational efficiency and profitability of the Taiwanese solar power industry between 2010 and 2011. According to the results of this study, only Motech, in 2010, was simultaneously operationally and profitably efficient. As the solar cell market expands, various input and output factors may be considered. When future studies are able to overcome data collection problems, the research period could be lengthened and additional data could be used to examine the developmental conditions of the solar power industry.

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