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Benefit Evaluation of Benchmarking Management: Case of Taiwan Semiconductor Industry

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Abstract

The main purpose of this study is to explore the carbon-reduction environmental benefits that can be achieved if benchmarking is used when Taiwanese semiconductor manufacturers are working to improve the technical efficiency of their carbon-reduction efforts. The evaluation method used is as follows. First, a technical efficiency measurement method capable of considering both desirable outputs and undesirable outputs is used to measure the technical efficiency of the carbon-reduction efforts, and to identify the benchmark firms with the best technical efficiency. Next, an attempt is made to estimate the greenhouse gas reduction that is realized by the sample if their carbon-reduction efforts are accompanied by the implementation of a benchmarking system. Finally, the monetary value of the greenhouse gas reduction is estimated, so as to develop a better understanding of the carbon-reduction benefits for the adoption of the process outlined above.

Keywords: technical efficiency, benchmarking, directional distance function, social cost of carbon

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1. Introduction

Following the enactment of the *Greenhouse Gas Emission Reduction and Management Act* (the "*Act*" henceforth) in Taiwan, it is anticipated that the general trend in government policy is toward the implementation of a cap-and-trade system for emission sources. Assuming that technology levels remain unchanged in the near future, the imposition of compulsory emission reduction requirements on industry implies that emission sources across many industries need to bear extra costs in their production processes in order to reduce greenhouse gas emissions. In other words, there will be a significant trade-off between production activity and carbon reduction measures. A key issue that needs to be addressed to reduce the magnitude of this trade-off between production activity and carbon reduction measures is the question of how to maintain the steady development of outputs from economic activity when still meeting carbon reduction targets. Among various approaches to tackling this issue, the key focus of attention for emission sources in many industries is, increasingly, the challenge of increasing the technical efficiency (TE) of management in emission source production processes, so that improvements in TE can be used both to fulfill the emission source's responsibilities to the environment and achieve continuous economic growth.

Conceptually speaking, what the TE indicator measures is the extent of the impact of the management techniques used by the decision-making unit (DMU) on the efficiency of production activities. That is, the higher a given DMU's TE is, the less factor inputs that DMU will require to achieve a specified level of output (or the more output can be achieved with a fixed quantity of factor inputs). TE is thus concerned with the enhanced production efficiency that can be brought about by a DMU's efforts in terms of improving its management.

TE measurement is widely used in management studies to address a wide range of production management related issues. As long as the inputs and outputs of production activity are defined, then it is possible to use TE measurement to evaluate whether or not a DMU has succeeded in improving its management. From a methodological perspective, of the many different TE empirical measurement techniques that have been developed, the distance function method has been particularly widely used because it does not require input/output price data (which can be difficult to obtain); only quantitative data are needed to measure the TE of specific DMUs. As regards output-oriented TE measurement, this mainly involves setting a fixed level of DMU inputs and then comparing the outputs of different DMUs; the DMU with the best performance is defined as the most efficient DMU. With this type of traditional measurement method, which assumes strong disposability, undesirable outputs like CO2 emissions equivalent (CO_2 henceforth) can be freely discarded without paying any price for them, and so they are usually left out of TE measurement with this method. As a consequence, TE values measured using the traditional distance function cannot reflect the impact on TE of the cost of dealing with undesirable outputs (Chung et al., 1997; Färe et al., 2001; Dyckhoff and Allen, 2001; Seiford and Zhu, 2002; Färe et al., 2005; Yang and Pollitt, 2007; Zhou et al., 2008; Färe et al., 2015; Hampf and Krüger, 2015).

To remedy the weaknesses of the distance function when it comes to measuring TE with undesirable outputs, previous research has proposed three alternative methods (Murty and Russell, 2002; Atkinson and Dorfman, 2002). All of these methods seek to measure the impact of undesirable outputs on TE. Of the three approaches, the directional distance function approach has emerged in recent years as the main method for measuring TE with undesirable outputs included, because it avoids the technical problems outlined above (Färe et al., 2001; Boyd et al., 2002; Lee et al., 2002; Färe et al., 2005; Arcelus and Arocena, 2005; Picazo-Tadeo et al., 2005; Färe et al., 2006; Kumar, 2006).

Specifically, the main focus of this study is the use of a TE method based on the directional distance function approach to measure the technical efficiency of carbon reduction management in one of Taiwan's key industries: the semiconductor industry. In addition, the study estimates the monetary value of the carbon reduction efforts, so that the results of carbon reduction can be presented in the form of an effectiveness indicator. This paper is structured as follows: following this Introduction, Section 2 explains the evaluation method used, Section 3 discusses the empirical data sources and the data processing procedures, Section 4 presents the empirical results and the analysis of these results, and Section 5 concludes this study.

2. Evaluation Method

2.1 Directional distance function

Within the traditional scope of the production economics field, discussion of output sets was initially focused on presenting possible relationships between factor inputs and desirable outputs. However, within a given production process, besides desirable outputs that create profits for the DMU, there may at the same time be undesirable outputs, i.e. various types of pollution that may be generated by production processes.

For production decision-making analysis, it is necessary for undesirable outputs to be incorporated into the analytical framework. The earliest attempt to improve the research method in this regard was the environmental production technology method proposed in Färe et al. (1989) to bring undesirable outputs into the output sets for analysis. The core concept here is the idea that the desirable outputs and undesirable outputs within the production process represent a kind of conjoint production; i.e. any increase in desirable outputs within the production process will inevitably be accompanied by undesirable outputs. The cost that must be borne in order to reduce these undesirable outputs may take one of two forms, depending on the actual circumstances. If the undesirable outputs are readily disposable, then reducing these undesirable outputs will not impose any significant costs. Taking pollution generated during the production process as an example, if the producer is located in a jurisdiction where environmental regulation is weak, then the producer can freely emit pollutants into the natural environment without paying any significant cost for this; in production theory, this is referred to as "strong disposability." The other possibility is that reducing the undesirable outputs does impose significant costs. For example, it may be necessary to reduce desirable outputs in order to control the increase in undesirable outputs, or to reallocate some of the resources that would otherwise have gone toward generating desirable outputs for use in the reduction of undesirable outputs; this is referred to as "weak dispensability."

In order to transform the above concepts into a useable analytical framework, Chung et al. (1997) proposed the concept of the "directional distance function" to describe the simultaneous impact of desirable outputs and undesirable outputs on the technical efficiency of production. As defined in Chung et al., the directional distance function for the output set P (X) can be expressed as follows:

$$\overrightarrow{D_0}(x, y, b; g) = max_{\beta}\{\beta: (y + \beta * g_y, b - \beta * g_b) \in P(x)\} \tag{1}$$

Where $g = (g_y, -g_b)$ is the direction vector, denoting the movement of the DMU's desirable outputs and undesirable outputs in such a way to achieve enhanced technical efficiency. β represents the rate in which the efficiency of the DMU is improved through the movement of desirable outputs and undesirable outputs in the direction vector $g = (g_y, -g_b)$, where β has a value ≥ 0. If, for example, DMU β_i has a value of 0.4 by comparison with the production boundary, then this indicates that the output set for this DMU must change to $(y + 0.4 * g_y, b - 0.4 * g_b)$ for it to be an efficient producer. This means that the larger the value of β_i is, the further the DMU is from the efficient production boundary, and the closer β_i is to 0, the nearer that DMU is to the efficient production boundary.

Chung et al. (1997) and later studies that make use of the directional distance function generally assumed that g = (1,-1). In terms of production decision-making behavior, this implies seeking to maximize desirable outputs from the production process, rather than seeking to minimize undesirable outputs, with desirable outputs increasing at the same rate that undesirable outputs decrease, i.e. $g_y = g_b = 1$. If management behavior is consistent with this analytical framework, it can be seen that the setting of the direction vectors g_y and g_b is used to delineate the impact of different types of management behavior on the output sets.

This idea can be explained by **Fig. 1** below. Assume an output set $P(x)$ which incorporates both desirable output y and undesirable output b, for a certain DMU, the current output set is $(y, b) = (x)$. If further assuming strong dispensability, then the output set should fall within the area outlined by points OEBCD. Regarding the potential room for increase in production efficiency, the DMU can move up from output set (x) to output set (x_2) using direction vector g = (1.0). If, on the other hand, controlling undesirable outputs incurs a cost, i.e. assuming weak dispensability, then the output set should fall within the area outlined by points OABCD, and improving TE will only move the output set from (x) to (x_3).

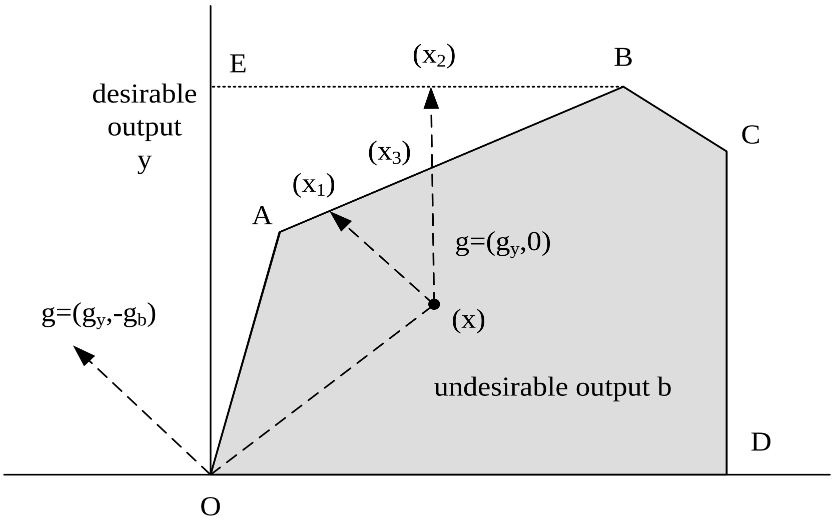

Fig. 1 Environmental production technology Output sets and the directional distance function

To obtain the TE of a DMU, the directional distance value needs to be converted into a function that can differentiate between b and y. We therefore adopt the method employed in Färe et al. (2006), using the quadratic approximation function for the directional distance function, utilizing a parametric estimation method to obtain a solution. We further use an approximation function that includes a desirable output (the output value indicator for the semiconductor indus), an undesirable output CO_2, and three factor inputs, as shown in equation (2) below:

$$\overrightarrow{D_0}(x, y, b; g) =$$
$$\alpha_0 + \sum\nolimits_{n=1}^{3} \alpha_n x_n + \beta_1 \mathrm{y} + \gamma_1 \mathrm{b} + \frac{1}{2} * \sum_{n=1}^{3} \sum_{n'=1}^{3} \propto_{n,n'} x_n x_{n'} + \frac{1}{2} * \beta_2 y^2 + \frac{1}{2} * \gamma_2 b^2$$
$$+ \sum_{n=1}^{3} v_n x_n b + uyb + \sum\nolimits_{n=1}^{3} \delta_n x_n y \tag{2}$$

To ensure that the translation properties of the directional distance function remain unchanged after conversion, equation (2) must conform to all the constraints listed in equation (3) below:

$$\beta_1 - \gamma_1 = -1,\ \beta_2 = \gamma_2 = \mu,\ \delta_n - v_n = 0,\ \alpha_{n,n'} = \alpha_{n'n},\ n, n' = 1,2,3. \tag{3}$$

where $\alpha,\ \beta,\ \gamma,\ v,\ \mu, \delta,$ are all unknown coefficients.

In the calculation, if we assume that there are k DMUs, then equation (2) can be solved using the (4-1) to (4-7) program shown below:

$$\min[\overrightarrow{D}_0\left(\overline{x_k}, y_k, b_k; 1, -1\right) - 1] \tag{4-1}$$
$$s.t.:\ \overrightarrow{D}_0\left(\overline{x_k}, y_k, b_k; 1, -1\right) \geq 0, k = 1, 2, 3....K \tag{4-2}$$
$$\partial \overrightarrow{D}_0\left(\overline{x_k}, y_k, b_k; 1, -1\right) / \partial y \leq 0, k = 1, 2, 3....K \tag{4-3}$$
$$\partial \overrightarrow{D}_0\left(\overline{x_k}, y_k, b_k; 1, -1\right) / \partial x \geq 0, k = 1, 2, 3....K. \tag{4-4}$$
$$\partial \overrightarrow{D}_0\left(x_k, y_k, b_k; 1, -1\right) / \partial b \geq 0, k = 1, 2, 3....K. \tag{4-5}$$
$$\partial^2 \overrightarrow{D}_0\left(x_k, y_k, b_k; 1, -1\right) / \partial y \partial b \leq 0, k = 1, 2, 3....K. \tag{4-6}$$
$$\partial^2 \overrightarrow{D}_0\left(x_k, y_k, b_k; 1, -1\right) / \partial y \partial y \leq 0, k = 1, 2, 3....K. \tag{4-7}$$

2.2 Social cost of carbon

An examination of the methods used in this field shows that, currently, the most widely used environment/cost benefit indicator for measuring reductions in greenhouse gas emissions is the social cost of carbon (SOC) (Interagency Working Group on Social Cost of Carbon, United States Government, 2010). In methodological terms, the SCC mainly employs a climate module Integrated Assessment Model (IAM) to implement assessment. The IAM model makes various assumptions with respect to the impact of climate change on the economy, e.g. assumptions regarding trends in greenhouse gas emissions, changes in global temperatures, and other possible effects of climate change, such as rising sea levels, changes in the intensity of precipitation, increased incidence of extreme weather events, etc. The IAM model can be used to gauge the losses that climate change from greenhouse gas emissions causes to society; this in turn can be used to provide a quantitative measurement of the costs incurred from every ton of CO_2 emissions, and the environmental benefits arising from every ton by which CO_2 emissions are reduced (United States Environmental Protection Agency, 2015).

As regards to the practical implementation of the SOC concept in relation to government policy, the U.S. government established an Interagency Working Group on Social Cost of Carbon (SCC) in 2009. The purpose of this Working Group was to calculate the monetary benefits for every ton by which CO_2 emissions are reduced; the Working Group published its first SCC Assessment Report in 2010 (Interagency Working Group on Social Cost of Carbon, United States Government, 2010), followed by a second report in 2013, and a revised third report in July 2015 (Interagency Working Group on Social Cost of Carbon, United States Government, 2015). The Working Group's reports mainly utilize the world's three mostly widely used IAM models – the Policy Analysis of the Greenhouse Effect PAGE) model (Hope, 2013), the Dynamic Integrated model of Climate and the Economy (DICE) model (Nordhaus and Sztorc, 2013), and the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) model (Anthoff and Tol, 2010) – to calculate the amount of harm caused globally by every ton of CO_2 emissions on the basis of a "global yardstick."

As the basis of calculation is global, and as the effects of CO_2 emissions are non-segmented, the figures given in the Working Group reports for the harm caused by CO_2 emissions are applicable globally (i.e. the impact on the Earth of one ton of emissions originating in Taiwan is the same as one ton of emissions originating in the U.S.). This means that "harm" in this case should not be taken to mean harm caused to any specific locality; rather, it represents the harm caused to the planet as a whole by excessively high emissions. Similarly, the social benefits deriving from efforts to reduce emissions are also global in scope, rather than being limited to a specific country. In calculating SCC, the Working Group first determines the values for SCC obtained with each of the three IAM models listed above, i.e. DICE, PAGE, and FUND, and then calculates the average of these values.

Calculation of the environmental benefits from the total amount of emission reduction is the multiplication of emissions reduction and its corresponding SCC value. SCC is not only widely used by the U.S. government when calculating the environmental benefits from emissions reduction policies, but is also used by many government agencies such as in the U.K. for assessing the effectiveness of government policies (Paul, 2013).[1] The basis of the method outlined above, this study uses the

[1] According to Paul (2013), British government agencies that use SCC for policy evaluation include the Department for Environment, Food and Rural Affairs (Defra), the Department for Transport (DFT), the

SCC method to evaluate the environmental benefits from carbon reduction from the implementation of benchmarking in the Taiwanese semiconductor industry.

3. Empirical Data Sources and Data Processing

The empirical analysis undertaken here requires data for input and output variables in the production processes of the Taiwanese semiconductor industry. There are two types of output variable to be considered. The first is desirable outputs, i.e. an indicator measuring the value of the products created during the production process that can provide economic benefits for the producer. This study uses the product sales revenue of individual semiconductor manufacturers for this indicator. The second type of output variable is undesirable output, which is defined as the volume of greenhouse gas emissions generated during the production process by the semiconductor industry. Past studies have generally used indicators such as capital stock, labor utilization, and cost of goods sold for input variables. Based on the available empirical data, this study then used labor factor costs, net capital, and cost of goods sold as the input variables.

As a result of policy planning requirements[2], the Environmental Protection Administration (EPA), Executive Yuan in Taiwan used a survey to collect variable data for firms in five targeted industries (including the semiconductor industry focused on here) in 2010; the data that firms were required to provide included energy usage data for different years, CO_2 emission volume calculated using the carbon emissions coefficient method, product output (calculated within the production boundary), etc. However, it is readily apparent from the data included in this EPA database that the specifications of the products manufactured by individual semiconductor firms vary significantly. For example, in the case of IC wafer products, the database records output of 6-inch, 8-inch, and 12-inch wafers, etc. Some firms may produce only one product type, while others may produce several. Given the difficulty in implementing assessment on the basis of a breakdown of product types, it was decided to sum together the CO_2 emissions totals for different product types to provide a single indicator for undesirable outputs.

Obtaining the data required for desirable outputs (i.e. product sales revenue) and

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Department for Trade and Industry (DTI), the Office of Gas and Electricity markets (OFGEM), the Office of the Deputy Prime Minister (OPDM), and the Environment Agency (EA).

[2] To encourage the private sector to implement voluntary emission reductions, the Environmental Protection Administration (EPA) launched the Early Action Project and Offset Project in 2010. Through participation in these two projects, firms could obtain emission credits, which could be offset against voluntary carbon neutralization commitments and greenhouse gas emission reduction commitments in relation to environmental impact assessments. Initially, the projects targeted firms in five industries: the cement industry, the iron and steel industry, the electric power industry, the LCD display industry, and the semiconductor industry.

for inputs was much more challenging, because there is lack of existing databases. To overcome this problem, a search of relevant data for stock-market-and OTC-listed companies available from Taiwan's Market Observation Post System (The Taiwan Stock Exchange Inc. & Taipei Exchange., 2016) was taken as the starting point; in addition, financial data for individual firms were collected for consecutive years, so as to provide the data needed for the desirable outputs and inputs variables. The main problem for firms' financial data is that the data included in the EPA database are structured by factory, not by company; to ensure consistency with the company-based financial data, the data for different factories belonging to the same company were added together. Following this data processing, the empirical data comprised data for nine semiconductor firms, with a total of 81 observations covering the period 2002 – 2010. To remove the impact of price fluctuations, data expressed in monetary terms were deflated using 2010 as the base year. A summary of the basic statistical results obtained is shown in **Table 1** below.

Table 1 Descriptive Statistics for Empirical Variables

Item	Net Sales Revenue (NT$ thousands)	CO_2 Emissions (tons/year)	Salary Expenses (NT$ thousands)	Net Fixed Assets (NT$ thousands)	Cost of Goods Sold (NT$ thousands)
Mean	63,772,080	764,782	5,942,103	72,425,693	46,193,426
Standard Deviation	85,105,759	846,953	7,513,427	74,004,984	47,390,512
Maximum Value	406,963,312	3,387,736	46,043,721	366,854,299	209,921,268
Minimum Value	2,704,741	48,714	819,357	1,945,441	2,876,877

Note: Data expressed in monetary terms were deflated using 2010 as the base year.

To evaluate the effectiveness of carbon reduction efforts, the SCC method was used. SCC data was derived mainly from a report prepared by the United States Environmental Protection Agency (2015). The SCC in the report covers the period 2015 – 2050. The results given for later years in this period have a high degree of uncertainty. This study then uses the SCC results for 2015 as the basis for calculation. On the basis of the SCC data shown in Appended Table 1, at discount rates of 5%, 3%, and 2.5%, the SCC for 2015 is calculated to be US$11, US$36, and US$56 respectively. Regarding the choice of discount rate, the Environmental Protection Administration, Executive Yuan (2014) suggested using the interest rate on 20-year government bonds as the discount rate indicator. The interest rate on government bonds in Taiwan in 2015 was 2.98% (Central Bank, 2015), which is closest to the 2.5% discount rate in the

SCC data, so it was decided to use the 2.5% discount rate for SCC data. That is, an SCC is equivalent to US$56 per ton as the basis for evaluation. With the average US$1 to New Taiwan Dollar NT$31.93 exchange rate in 2015 (Central Bank, 2016), the SCC is equal to NT$1,788 per ton.

4. Discussions of Empirical Results

The General Algebraic Modeling Systems (GAMS) software was used in combination with a non-linear algorithm method to estimate the results of equations (4-1) to (4-7); the coefficient estimation results are then transposed into equation (2) to estimate the TE value of each DMU. The directional distance function estimation results are shown in **Table 2**. Finally, the TE value was used to calculate the carbon reduction results and increase in revenue that could be achieved if a given firm learned from the management techniques used by a benchmark firm; a summary of the results is shown in **Table 3**.

Regarding the interpretation of the calculation results, the TE value represents the efficiency of the carbon reduction techniques used calculated by the directional distance function method. The closer the TE value is to zero, the more efficient the production techniques used are; the further away the TE value is from zero, the greater the gap between the performance of the DMU and that of the benchmark firm. This phenomenon indicates that there is considerable room for improvement. The empirical estimation results show that 14 of the DMUs had a TE value of zero. This shows that the DMUs of this study displayed the best performance in terms of the TE of carbon reduction management for the 81 sampling points and were therefore designated as the benchmark firms. The TE values for the other DMUs were calculated by comparison with these benchmark DMUs.

For instance, if a given DMU is calculated to have a TE value of 0.02, then this indicates that, by comparison with the benchmark DMUs, this DMU has room to achieve a 2% increase in revenue and a 2% decrease in CO2 emissions. In managerial terms, if the DMU learns emissions management techniques from a benchmark DMU of similar size, then it can boost its overall revenue by 2%, at the same time adjusting its production processes to realize a 2% reduction in CO_2 emissions. Based upon the empirical results obtained in this study, the mean TE value for the sample can be calculated to be 0.1605. This indicates that, on average, the 81 DMUs that constitute the sample could achieve an average reduction in emissions of 16.05% and an average increase in revenue of 16.05%. In absolute terms, each DMU can boost its sales revenue by about NT$66 billion per year through benchmarking, on average, and at the same time reduce annual emissions (per DMU) by 88,743 tons of CO_2. In terms of the total impact, the total increase in revenue deriving from the increased TE value would be about NT$533.7 billion per year, and the total reduction in CO_2 emissions would be 7,188,168 tons per year (it should be noted that, as 14 of the DMUs are designated as benchmark DMUs, it is only the remaining 67 DMUs that would see an improvement in TE).

Table 2 Coefficient Estimation of Directional Distance Function

Coefficient	Variable	Coefficient Estimation
α_0	Constant term	0.328
α_1	Salary expenses (x_1)	0.059
α_2	Net fixed assets (x_2)	-0.013
α_3	Cost of goods sold (x_3)	0.207
β_1	Real GDP(y)	-0.650
$\gamma_1 = \beta_1 + 1$	CO_2 emissions (b)	0.350
α_{11}	x_1^2	-0.130
α_{12}	$x_1 x_2$	-0.039
α_{13}	$x_1 x_3$	-0.086
α_{22}	x_2^2	0.061
α_{23}	$x_2 x_3$	-0.049
α_{33}	x_3^2	-0.018
$\beta_2 = \mu = \gamma_2$	y^2, yb, b^2	-0.081
$\delta_1 = \nu_1$	$x_1 y, x_1 b$	0.166
$\delta_2 = \nu_2$	$x_2 y, x_2 b$	0.023
$\delta_3 = \nu_3$	$x_3 y, x_3 b$	0.030

Having completed the calculations outlined above, it is now possible to determine the reduction in annual CO_2 emissions that semiconductor firms can obtain through benchmarking. Using an estimated value of the benefits from carbon reduction per unit of SCC under the baseline year 2015, the benefits from carbon reduction (in monetary terms) resulting from the raising of the TE of each DMU can thus be estimated. Since the SCC per ton of CO_2 is NT$1,788, using this magnitude together with the reduction in CO_2 emissions deriving from the improvement in TE achieved through benchmarking, it is possible to calculate the benefits from carbon reduction.

On the basis of the estimation results shown in **Table 3** above, if each DMU uses benchmarking to learn superior emission management techniques from the benchmark firms, then on average the resulting improvement in the efficiency of carbon reduction techniques will provide each DMU with carbon reduction benefits that, in monetary terms, equate to about NT$1.6 billion per year. Overall, the combined benefits to the 36 DMUs that achieve an increase in TE will total about NT$12.9 billion per year.

Table 3 Summary of TE Estimation Results

Item	TE Vale	Increase in Revenue from TE Improvement (NT$ thousands / year)	Reduction in CO_2 Emissions from TE Improvement (tons / year)	Value of Reduction in CO_2 Emissions from TE Improvement (NT$ thousands / year)
Mean	0.1607	6,588,383	88,743	158,672
Standard Deviation	0.1325	6,655,098	95,476	170,712
Maximum Value	0.68	24,537,944	363,046	649,126
Minimum Value	0	0	0	0

Note: Data expressed in monetary terms were deflated using 2010 as the base year.

5. Conclusion

Utilizing the directional distance function method to measure the technical efficiency (TE) of carbon reduction, this study seeks to measure carbon reduction TE in the Taiwanese semiconductor industry. With measurement of TE, the study goes on to integrate the social cost of carbon (SOC) methodology in calculating the monetary terms of carbon reduction benefits from the improvement in carbon reduction TE.

On the basis of the estimation results obtained in the study, 14 of the 81 decision-making units (DMUs) included in the sample are selected as benchmark DMUs. This indicates that these 14 DMUs have technical efficiency superior to that of the other 67 DMUs. By performing estimation of the directional distance function, it is possible to calculate the efficiency gap between these 67 DMUs and the benchmark DMUs. From a policy-making perspective, the significance of this is that there is significant room for these 67 DMUs to improve their management techniques and methods (as opposed to their level of production technology) by bringing them up to the level of the benchmark DMUs. Assuming that there is no significant disparity between the DMUs in terms of the achievable level of production technology, then if benchmarking is performed for the 67 DMUs with lower TE, once the TE of their carbon reduction management has been raised to a level comparable to that of the benchmark DMUs, it should be possible to realize both a significant increase in revenue and a significant reduction in CO_2 emissions.

Based on the empirical estimation results obtained in this study, it can be seen that using benchmarking to raise the TE of carbon reduction management would, on average, boost the annual sales revenue of each DMU by about NT$66 billion, while also reducing the average annual CO_2 emissions per DMU by 88,743 tons. Overall, the combined increase in revenue for all the semiconductor firms included in the study would total NT$533.7 billion per year, and the combined reduction in CO_2 emissions would total 7,188,168 tons. As regards the benefits from carbon reduction, the average carbon reduction benefits for each DMU would amount to approximately NT$1.6 billion per year; overall, the combined carbon reduction benefits for all 36 DMUs included in the sample would be about NT$12.9 billion per year.

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