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Evaluating Performance of IC Packaging and Testing Firms by Bootstrap Data Envelopment Analysis

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Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

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ABSTRACT

Taiwan's Integrated Circuit Packaging and Testing (ICPT) industry ranks number one in the world with 56% market share. However, facing the keen competition from global market, enhancing the operating performance becomes the most important way to be survival. As such measuring the efficiency deserves in-depth investigation. This paper adopts DEA and Bootstrap DEA methods to evaluate the performance for 24 global ICPT companies in 2010. The results show that, the average bias-corrected efficiency is slightly less than DEA efficiency. Based on the results some conclusions are drawn and recommendations for improving performance as well as the future study are proposed.

Keywords: Data Envelopment Analysis (DEA); Bootstrap Data Envelopment Analysis (BDEA); IC packaging and testing.

JEL: C02, C61, D22

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1. INTRODUCTION

Driven by a quick recovery of the global economy in 2010, coupled with the substantial growth of smart phones, and other portable electronic devices, the output value of world's integrated circuit packaging and testing industry (ICPT) reached 47 billion U.S. dollars, and the annual growth rate was 23.8% [1]. With 56% market share, Taiwan's ICPT industry ranks number one in the world, and three out of the global top five ICPT corporations are from Taiwan. However, influenced by such natural disasters as Japanese earthquake, Thailand flooding, and European sovereign debt crisis, the global economic visibility decreased and the strength of end demand growth has experienced recession since the second half of 2010. Furthermore, Taiwan's ICPT firms also face keen competition from China, Malaysia, Singapore and South Korea. As such, measuring and comparing the operating efficiency for ICPT worldwide firms deserve in-depth investigation.

It is well known that data envelopment analysis (DEA) is a linear programming technique for estimating the relative efficiency of decision making units (DMUs) that perform the same tasks in a production system. Since it was firstly proposed by Charnes et al. [2], and succeeded by Banker et al. [3], various DEA approaches have been widely applied for the efficiency evaluation throughout different industries, including public and private sectors. Since DEA possesses many advantages such as it can be used to deal with performance evaluation for multiple-output multiple-input firms; it is no need to specify a functional form to portray the relationship between inputs and outputs in prior. In this paper we thus adopt DEA to evaluate the operating efficiency for some selected 24 global ICPT companies in the year of 2010. We choose gross sales as output, and select total assets, the number of employees, and operating expenses as input variables. Moreover, traditional DEA (TDEA) models are attributed to deterministic frontier method, and have often been criticized for not taking into account statistical noise and lacking any hypothesis testing. In addition the DEA efficiency in general is upward-biased. Recently, many researchers have addressed this issue, for example Simar and Wilson [4-6] proposed to use the Bootstrap DEA (hereinafter, BDEA) to derive the bias-corrected DEA efficiency and confidence intervals for the samples. The basic idea of BDEA is based on the concept of sampling replication from the data, which is originally developed by Efron [7] and extended by Efron and Tibshirani [8]. The methods of TDEA and BDEA used in this study will be elaborated in Section 3.

The remaining part of this article is organized as follows. Section 2 briefly depicts the manufacturing process of integrated circuit and reviews some of previous works. Section 3 elaborates the methodologies used in this study, including traditional DEA models and bootstrap DEA approach. The empirical results and some further discussions based on the results are described in detail in section 4. Finally, the concluding remarks and possible avenues of future study are provided in section 5.

2. LITERATURE REVIEW

The manufacturing processes of integrated circuit, as shown in Fig. 1, consist of design, mask, foundry segment manufacturing, packaging and testing. The development of Taiwan's semiconductor industry began in 1966. Nowadays, as we mentioned in previous section, Taiwan's IC industry plays an important role in the worldwide supply chain system, especially in foundry segment manufacturing, packaging and testing. In this paper we are focusing only on the packaging and testing industry, more specifically, we are attempting to evaluate the performance for some selected 24 worldwide ICPT firms. Before doing so it is important to review the relevant previous works in the literature, which can be briefly described as follows.

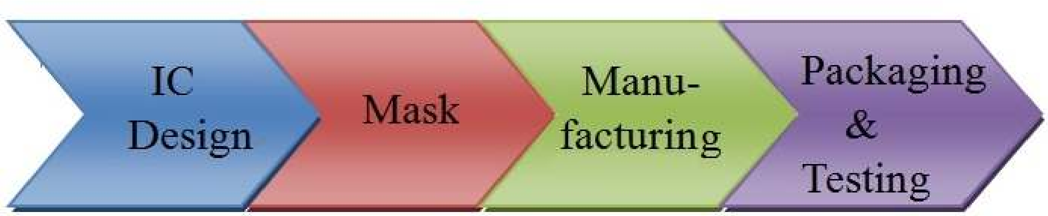

Fig. 1. IC manufacturing process

Inspired by Fried et al. [9,10], Huang and Huang [11] evaluated the total factor productivity growth of Taiwanese semiconductor companies, including design, manufacturing, packaging and testing, and then decomposed it into four components, namely: efficiency change, technical change, scale efficiency change, and total factor productivity change, by a three-stage Malmquist DEA panel model. The empirical results show that the environmental factors have affected efficiency evaluation significantly. The results also indicate that Taiwanese semiconductor industry has experienced efficiency improvement, technical progress and productivity growth in 2002-2007. Meanwhile, the results also confirmed that productivity growth and technological change (efficiency change) are overestimated (underestimated) if environmental factors are ignored.

Liu and Wang [12] also employed DEA-like method to measure the Malmquist Productivity Index (MPI) for 15 Taiwan's ICPT firms from 2000 to 2003. The input variable used in their analysis is liability ratio, and output variables are growth rate (%), net profit after tax, profitability ratio (%), and output value by employee. When calculating 4 distance function in MPI measurement, instead of radial-based (that is CCR) model in previous works, they adopted slacks-based measurement (SBM) model and super SBM model developed by Tone [13,14]. Comparison is made between the results from SBM/Super-SBM and CCR models. Since the slacks are taken into account in the analysis of SBM/Super-SBM models, the authors thus concluded that the results of using proposed model are more precise than traditional one.

Chen, et al. [15] utilized DEA method to evaluate the efficiency of fabrication facilities. In order to defines and illustrates the "real" performance and the non-production problem, this paper developed two-stage model to measure the overall performance score when considering diffident side. The DMU of this paper is four different fabrication facilities within the same company. The empirical result shows that the two-stage model can provide clear picture on production sites performance and better interpretation on performance difference.

Shen, et al. [16] also adopted DEA method and Malmquist index model to measure production performance and productivity of 10 semiconductor assembly plants. They use average employee number, average labor hours, and cost of goods sold as input factors; production output, average overall equipment effectiveness, production cycle time, and production ratio as output variables. The application results show that technology inefficiency is due to unsuitable resource allocation in the side of operation efficiency. This paper also indicates the reason of the relatively inefficient factories is because number of employees may use additional hidden costs and wastes by using slack variable analysis and sensitivity analysis.

Lo and Tzeng [17] measure the performance of 9 semiconductor manufacturing operation fab-line in Taiwan in the year of 1999-2001 by using DEA model and the new DEA Fuzzy Multiple Objective Programming (FMOP) approach. They use salary, cost of goods, chamber, stepmove, patent, and margin as input variable, wafer out as only output. The results show that, 7 DMUs are evaluated as efficient based on the assumption of CCR model, 9 DMUs were efficient in BCC approach. They also try to combine different output factors to notice that it is more closely approximate the real side.

Jain, et al. [18] adopted DEA approach to measure the performance and target setting of a wafer manufacturing while two different manufacturing environments. The DMU of this paper is 51 weeks of the wafer manufacturing, and separating 2 parts. The estimated results shows 33 out of 51 weeks were inefficient, and the number of inefficient of first part is more than second part. Finally, this paper gives the wafer manufacturing some decision supports.

To sum up, at least three features can be found in the previous studies. First of all, although DEA methods are widely used for performance evaluation of a number of industries, such as hospital (Tan and Wang, [19]; Kazley and Ozcan, [20]), university (Li, [21]), electricity generation and distribution (Arocena, [22]), transportation (Yu and Lin, [23]) and banking industries (Maghyereh and Awartani, [24]), however, application of DEA to high-tech, especially to ICPT, seems relatively few. Secondly, there exists at least one shortcoming in the aspect of variable selection in previous researches. As mentioned by Golany and Roll [25], introduction of too many, especially redundant, variables oftentimes tend to shift the compared units toward the efficiency frontier, resulting in relatively large number of units with high efficiency scores. Thus, before conducting the DEA-based analysis, one needs to check and select variables very carefully. Some variables such as growth rate, net profit after tax, profitability ratio, and output value by employee in Liu and Wang [12], may be repeating virtually the same or similar information, thus should not be included in the analysis simultaneously. Finally, the traditional DEA models neither take into account statistical noise nor allow hypothesis testing, and the DEA method often overestimates the technical efficiency of firms under study. However, scarce researchers paid their attention on the application BDEA to performance evaluation for ICPT industry. To fill this gap, we thus employ BDEA to estimate bias-corrected technical efficiency and derive the confidence interval of efficiency for the 24 ICPT firms. The methodologies used in this analysis, including TDEA and BDEA models will be elaborated in the following section.

3. METHODOLOGY

3.1 DEA Models

In production economics context, production technology can be represented by the production possibility set containing all feasible input and output vectors: $T=\{(x,y) \mid x \text{ can produce } y\}$. That is, one can define output set $P(x)$ as $P(x) = \{y \mid (x,y) \in T\}$. Or, alternatively, one can define input set $L(y)$ as $L(y)= \{x: \mid (x,y) \in T\}$, where $x = (x_1, x_2,\ldots,x_m) \in R_+^m$, and $y = (y_1, y_2,\ldots,y_k) \in R_+^k$. Both $P(x)$ and $L(y)$ are closed and bounded, and satisfy strong disposability. Once the output set (or input set) has been defined, the efficiency can be measured by the distance from observed data point to the best practice (frontier), which can be solved by using linear programming technique. Assume that there are J decision-making units (DMUs) to be evaluated, $J=\{1,\ldots,J\}$, each DMU produces K outputs $K=\{1,\ldots,K\}$, by utilizing M inputs, $M=\{1,\ldots,M\}$. The output-oriented CCR DEA model can be written as follows (Charnes, et al. [2]).

$$
\begin{aligned}
& Max_{\phi,\lambda}\phi_i \\
& s.t.\ \ -\phi_i \cdot y_{ik} + \sum_{j=1}^{J}\lambda_j y_{jk} \geq 0,\ k=1,...,K, \\
& \quad x_{im} - \sum_{j=1}^{J}\lambda_j x_{jm} \geq 0,\ m=1,...,M, \\
& \quad \lambda \geq 0,\ j=1,...,J
\end{aligned}
\tag{1}
$$

Where, λ is scalar and $1/\phi_i$ is the efficiency of DMU$_i$ to be estimated, x and y denote the input and output variables, respectively. The objective of model (1) is to find the maximal output expansion ratio, keeping all inputs unchanged. The ϕ_i is calculated by solving model (1) once for each firm in the sample. The model (1) implicitly assumes that all DMUs produce their outputs under the situation of constant returns to scale, which may not be in line with the actual practice of production; Banker, Charnes, and Cooper (BCC, [3]) thus relaxed the assumption by adding an extra convexity constraint, that is, $\sum\lambda=1$, into the model (1). The model then becomes:

$$
\begin{aligned}
& Max_{\phi,\lambda}\phi_i \\
& s.t.\ \ -\phi_i \cdot y_{ik} + \sum_{j=1}^{J}\lambda_j y_{jk} \geq 0,\ k=1,...,K, \\
& \quad x_{im} - \sum_{j=1}^{J}\lambda_j x_{jm} \geq 0,\ m=1,...,M, \\
& \quad \sum_{j=1}^{J}\lambda_j = 1, \\
& \quad \lambda \geq 0,\ j=1,...,J
\end{aligned}
\tag{2}
$$

Once the technical efficiency scores based on model (1) and (2) have been calculated, the scale efficiency, (SE) can be obtained by dividing objective of model (2) by that computed from model (2), that is, $SE = \phi_{BCC}/\phi_{CCR}$, SE = 1 indicates scale efficient and SE < 1 represents scale inefficient. In the case of scale inefficient, it can be further classified into increasing returns to scale (IRS) and decreasing returns to scale (DRS) by observing the summation of λ obtained from model (1), the DMU under estimated will exhibits IRS (DRS) if summation of λ is less (greater) than unity. For more detail, refer to Banker [26].

3.2 Bootstrap DEA Method

Both CCR and BCC models are attributed to deterministic estimators which are based on a finite sample of observed production units, the corresponding measures of efficiency scores are sensitivity to the sampling data, Simar and Wilson [4] thus proposed a general methodology of bootstrapping in nonparametric frontier models by following the concept developed by Efron [7].

The method proposed by Simar and Wilson [4] is based on the idea of resampling a lot of times and applying the DEA estimator to each of resampling data sets so that one can mimic the sampling distribution and the resulting efficiency scores seem more precise and reliable. In this paper, we attempt to estimate technical efficiency obtain the confidence intervals of efficiency for 24 IC packaging and testing companies, we thus apply bootstrap method by following Simar and Wilson [4], which can be described as follows.

In general the production possibility set *T*, output set *P* (*x*), and the best practice (or frontier) mentioned in subsection 3.1, are unknown, but one can still obtain the BCC technical efficiency scores by observed data and using model (2), denote the efficiency by $\hat{\phi}_j, (j=1,2,...,J)$. By using some data generating process (DGP), one can generate a random sample output set P^* (*x*) and obtains the corresponding measure of efficiency. Repeat the procedure B times and denote the bootstrapping DEA efficiency score by $\hat{\phi}^*_{j,b}$ (b=1,2,…, B, $j=1,2,...,J)$. Note that $\hat{\phi}^*_{j,b}$ is generated from $\hat{\phi}_j, (j=1,2,...,J)$ as follows, for more detail refer Simar and Wilson [4].

a. Given the set of calculated DEA efficiency indices, $\hat{\phi}_1, \hat{\phi}_2, ..., \hat{\phi}_J$, obtain the bandwidth parameter *h* such that $h = 0.9n^{-1/5} \cdot \min\left\{\sigma_{\hat{\theta}}, R_{13}/1.34\right\}$ where $\hat{\sigma}_{\hat{\phi}}$ denotes the plug-in standard deviation of the DEA efficiency $\hat{\phi}_1, \hat{\phi}_2, ..., \hat{\phi}_J$, and R_{13} denotes the interquartile range of the empirical distribution of $\hat{\phi}_1, \hat{\phi}_2, ..., \hat{\phi}_J$.
b. Generate $\beta^*_{1,b}, \beta^*_{2,b}, ..., \beta^*_{n,b}$, by resampling with replacement from the empirical distribution of $\phi^*_{1,b}, \phi^*_{2,b}, ..., \phi^*_{J,b}$.
c. Smooth the sampled values $\tilde{\phi}^*_1, \tilde{\phi}^*_2, ..., \tilde{\phi}^*_n$, using the following:

$$\tilde{\phi}^*_1 = \begin{cases} \beta^*_j + h\cdot\varepsilon^*_j, \ if \ \beta^*_j + h\cdot\varepsilon^*_j \geq 1, \\ 2-(\beta^*_j + h\cdot\varepsilon^*_j), \ if \ \beta^*_j + h\cdot\varepsilon^*_j < 1 \end{cases}$$

$$j = 1,2,..., J$$

d. Define the bootstrap sequence $\phi^*_{1,b}, \phi^*_{2,b}, ..., \phi^*_{J,b}$. using the following:

$$\phi^*_{j,b} = \overline{\beta}^*_b + \frac{1}{\sqrt{1+h^2/\hat{\sigma}_{\hat{\theta}}}} \cdot (\tilde{\phi}^*_j - \overline{\beta}^*_b), j=1,2,...,n,$$

$$where, \ \overline{\beta}^*_b = \left(\frac{1}{n}\right)\sum_{j=1}^{n}\beta^*_{j,b}, \text{ and } n \text{ is the number of firms}$$

Compute the bootstrap pseudo-sample data $(x, y^*_{j,b}), j=1,2,...,\mathrm{J}$ using the following: $(x, y^*_{j,b}) = \left(x, \phi^*_{j,b}\cdot y^f_j\right)$

e. Compute the bootstrap DEA efficiency $\hat{\phi}^*_{j,b}$, for j=1,2,…,J, using the pseudo-sample data and the following linear program:

$$\begin{aligned} & Max\phi^*_{k,b} = \phi + \varepsilon(s^+ + s^-) \\ & s.t. \\ & Y^*_b\cdot\lambda - s^+ = \phi\cdot y_k, \\ & x_k - X\cdot\lambda - s^- = 0, \\ & \lambda, s^+, s^- \geq 0 \end{aligned}$$

where,

$Y^*_b = (y^*_{1,b}, y^*_{2,b}, ..., y^*_{J,b})$, is *s*×*J* matrix of observed output data, and
$X = (x_1, x_2, ..., x_J)$ is *m*×*J* matrix of observed input data.
λ, (*J*×1) vector of intensity variables for all DMU,
s^+ (*s*×1) vector of output slack variables,
s^- (*m*×1) vector of input slack variables.
f. Until b=B, repeat steps (a)-(f) to provide for *j*=1,2,…,*J*, a set of bootstrapped efficiency scores, $\left\{\phi^*_{j,b}, b=1,2,...,B\right\}$

The estimated bias, $bias_j$ of the DEA efficiency score $\hat{\phi}_j$ for the *j*th DMU is

$$bias_j = \frac{1}{B}\sum_{b=1}^{B}\hat{\phi}^*_{j,b} - \hat{\phi}_j \qquad (3)$$

Where, $\hat{\phi}_j$ is the j^{th} DMU's DEA efficiency score calculated from model (2), $\hat{\phi}^*_{j,b}$ be the b^{th} bootstrap DEA efficiency for the j^{th} DMU, and B is the number of bootstrap replications.

The bias-corrected DEA efficiency for the j^{th} DMU ($\tilde{\phi}_j$) is

$$\tilde{\phi}_j = \hat{\phi}_j - bias_j \tag{4}$$

The standard error of $\hat{\phi}_j$ may be estimated by

$$\hat{se} = \left\{ \frac{1}{B-1} \sum_{b=1}^{B} (\hat{\phi}^*_{j,b} - \bar{\phi}^*_j)^2 \right\}^{\frac{1}{2}} \tag{5}$$

The percentile method (Efron and Tibshirani, [8]) is the most straightforward method to obtain the bootstrap confidence intervals, which is based on the empirical cumulative distribution function $\hat{G}$ of $\tilde{\phi}^*_{k,b}$. The (1-2α) percentile confidence interval is given by ($\tilde{\phi}^{*(\alpha)}_{k,}$,$\tilde{\phi}^{*(1-\alpha)}_{k,}$), where $\tilde{\phi}^{*(\alpha)}_{k,}$ indicates the α percentile of $\hat{G}$.

4. EMPIRICAL ANALYSIS

4.1 The ICPT Industry

In the recent several years, ICPT industry becomes more and more important because of substantial growth of communication and consumer electronic products. In addition, due mainly to curtailing the cost, the integrated device manufacturers are tending to outsource their IC package and test, including design and manufacturing businesses to service providers in the world. As a consequence, the ICPT industry has grown significantly in terms of revenue in the year of 2011. Table 1 indicates the ranking, revenue and market share of top 20 firms in the world in 2011. As one can see from Table 1, ASE, SPIL, and Powertech (all headquartered in Taiwan) are ranked top 1, 3, and 5, respectively, while Amkor (American based firm) is ranked as number 2 in the world.

4.2 The Data

As we mentioned in previous section, when employing DEA to measure the relative efficiency of decision making units (DMU), it is very important to determine the input and output variables to be included in the analysis. A DMU converts the resources to produce outputs, as such all inputs and outputs should be included in

Table 1. Rank and revenue of ICPT firms in 2011 (Source: IEK [27])

Rank	Company	Region	Revenue	Market share
1	ASE	Taiwan	4,252	17.7%
2	Amkor Technology	United States	2,776	11.6%
3	SPIL	Taiwan	2,024	8.4%
4	STATS ChipPAC	Singapore	1,707	7.1%
5	Powertech Technology	Taiwan	1,252	5.2%
6	UTAC	Singapore	981	4.1%
7	ChipMOS Technologies	Taiwan	620	2.6%
8	Jiangsu Changjiang Electronics Technology	China	611	2.5%
9	J-Devices	Japan	565	2.4%
10	Chipbond Technology	Taiwan	441	1.8%
11	STS Semiconductor	South Korea	428	1.8%
12	Formosa Advanced Technologies	Taiwan	404	1.7%
13	King Yuan Electronics	Taiwan	385	1.6%
14	Unisem	Malaysia	380	1.6%
15	Carsem Semiconductor	Malaysia	360	1.5%
16	Greatek	Taiwan	290	1.2%
17	Walton Advanced Engineering	Taiwan	260	1.1%
18	AOI Electronics	Japan	257	1.1%
19	Nantong Fujitsu Microelectronics	China	251	1.0%
20	Signetics	South Korea	250	1.0%

the analysis (Boussofiane et al. [28]). In order to producing the packaging and testing services, some special equipment are in general needed, especially for testing process. In other words, ICPT is commonly attributed to capital-intensive industry. We thus choose the total assets as one of input variable. Based on some previous studies and in line with underlying of production economics, the number of employees and operating expenses are selected as two additional input variables. As for the output, the ICPT firms in general produce two outputs, namely: Packaging and testing, however, the quantities of the two outputs are not available. In such case, the company's gross sales would be a good proxy for representing production of firm's packaging and testing operations, therefore is included in the analysis. Table 2 shows the definition and unit of each input and output variables.

Our data set is drawn from 2010 annual report published online by each of sampling companies. Note that when applying DEA to evaluate the efficiency, the DMU under consideration should be homogeneous. In this study we attempt to analyze the efficiency for worldwide ICPT industry, we thus choose 24 firms as our sample. All of these firms provide both packaging and testing services globally. Of which 16 firms come from top 20 companies listed in Table 1. Those firms without complete operation data, such as UTAC, J-Devices, Carsem, and Signetics, are excluded from our data set. To make comparison sense, we thus enhance our data set by adding 8 companies; all are listed in Taiwan stock market. As a result totally there are 24 DMUs in our data set. Although we do not include all firms in the world's ICPT industry, these 24 firms in fact took a large share of the entire industry – over 81 percent in terms of gross sales of global industry in the sampling year which is sufficiently large to represent the entire ICPT industry in the world. Table 3 summarizes the descriptive statistics of the data, including three inputs and one output. From Table 3 one can easily find that the data are rather heterogeneous. Taking total assets as an example, the data ranges from 68 to 5,548 million US dollars, and the standard deviation is 1,251 million US dollars. It reveals that the operating scales of each firm are quite varied; thus we must consider the effects of scale on the variation of efficiency.

Furthermore, since DEA approach initiated by Farrell [29] and developed by Charnes et al. [2] and Banker et al. [3] is based on the underlying theory of production economics, therefore the inputs and outputs included in DEA analysis should satisfy the condition of isotonicity. The so-called isotonicity is the requirement that the relationship between inputs and outputs should not be exotics. Increasing the amount of any input while keeping other factors constant should not decrease any output but instead should lead to an increase in at least one of outputs. This can be investigated by conducting the calculation of all inter-correlation between inputs and outputs. The results are displayed in Table 4, from which we see that positive and significant correlations at level of significance, $\alpha = 0.05$, so that the condition of isotonicity is satisfied and the inclusion of inputs and output in our analysis is justified.

4.3 The Results

We estimate efficiency scores for 24 world's ICPT firms by both TDEA models and BDEA methods. The former is performed by utilizing the EMS software, developed by Scheel [31]; while the latter is carried out by FEAR, developed by Wilson [32]. The results are indicated in Table 5 (TDEA models) and Table 6 (BDEA model). Based on the results and further analysis, some important findings are summarized and discussed as follows.

Table 2. Definition of input and output variables

Catogories	Variable	Units	Definition
Input	Total assets	Million US dollars	The sum of all cash, investments, furniture, fixtures, equipment, receivables, intangibles, and any other items of value owned by a person or a business entity. (Source: [30])
	Number of employees	People	workers hired by each company.
	Operating expenses	Million US dollars	An ongoing cost for running a product, business, or system, with exclusion wage and salary.
Output	Gross sales	Million US dollars	The sum of all sales during a time period

Table 3. Descriptive statistics of input and output variables

Variable	Gross sales	Number of employees	Total assets	Operating expenses
Max	4,222	19,900	5,548	3,207
Min	68	246	68	104
Mean	756	5,183	1,015	598
S.D.	1,016	5,493	1,251	783

Note: units for each of variables are same as in Table 2

Table 4. Correlation coefficient of input and output variables

	Number of employees	Total assets	Operating expenses	Gross sales
Number of employees	1			
Total assets	0.84	1		
Operating expenses	0.88	0.97	1	
Gross sales	0.89	0.98	1	1

4.3.1 TDEA

From Table 5, one can see that based on the assumption of CRS the average efficiency of 24 ICPT companies is 1.206, implying that on average all firms should expand their output by 20.6 percent keeping all inputs unchanged so as to be efficient. 5 DMUs, Amkor, Powertech, STS, Unisem, and Xintec are evaluated as technically efficient. Meanwhile remaining 19 firms are attributed to be inefficient, of which the most inefficient DMU is Nantong Fujitsu with efficiency score 1.587, followed by ChipMOS, Walton Advanced, OSE, and SPIL.

Also from Table 5, when using the BCC model which is based on the assumption of VRS, 8 DMUs, Amkor, Powertech, STS, Unisem, Xintec, ASE, Stack Devices and Aptos are evaluated as efficient, while remaining 16 firms are inefficient with scores ranging from 1.007 to 1.457. The most inefficient company is Nantong Fujitsu with efficiency score of 1.457; followed by ChipMOS (1.438), OSE (1.354), and Walton Advanced (1.310). On average the efficiency score of sampling ICPT firms is 1.134. The policy implication is that those inefficiency DMUs should increase their output by 13.4 percent, taking all firms as a whole.

As for the scale efficiency, from Table 5 one can easily see that the average scale efficiency score is 0.947. 5 DMUs, Amkor, Powertech, STS, Unisem, and Xintec produce their output under constant returns to scale or optimal scale size. 6 (13) of remaining 19 scale inefficient DMUs are attributed to increasing (decreasing) returns to scale. It should be noted that, those DMUs attributed to decreasing returns to scale are in general larger scale firms in terms of total assets. Since DEA is a powerful method to measure the operating efficiency and detect the source of inefficiency, therefore, for those evaluated as scale inefficient firms, one of possible avenues for improving performance is to adjust their production size. Taking SPIL as an example, the aggregate efficiency (CCR) is 1.354 and pure technical efficiency (BCC) is 1.149, resulting in the scale efficiency of 0.849 (=1.149/1.354), which is due to decreasing returns to scale. Our empirical result indicates that its aggregate inefficiency comes from both technical and scale. Therefore, the possible way for improving performance is downsizing production scale, in addition to adjusting manufacturing processes.

To examine the effect of scale on efficiency, the samples are classified into two categories by total assets, namely larger and smaller groups. By using cluster analysis and R software, the result indicates that DMU 1 to DMU 5 can be attributed to larger group while the others are ascribed to smaller one. In general, those firms with total assets greater than USD 1,500 billion are attributed to larger category. The average technical efficiencies of larger and smaller groups based on the assumption of VRS are 1.048 and 1.160, respectively. The result of t-ratio test reveals that the null hypothesis of no efficiency difference can be rejected with 5% level of significance, that is, on average the technical efficiency of larger firm is significantly higher than that of smaller one. This finding is consistent with underlying theory of economics and the fact of larger firms in general with competitive advantage due to scale effect.

As mentioned earlier, Taiwan's ICPT firms play a very important role in the global industry, to investigate whether Taiwan's firms are more efficient than non-Taiwan's firms, we thus classify the samples into two groups. Based on the assumption of VRS, the average pure technical efficiency of Taiwan's firm is 1.14, while for non-Taiwan is 1.13. The result of t-ratio test indicates that the null hypothesis of no difference between the two groups cannot be rejected.

4.3.2 BDEA

In this study, we adopt FEAR [32] to estimate BDEA efficiency of 24 worldwide ICPT firms. FEAR is based on the general-purpose statistical package R and can be downloaded freely from Wilson's website. By resampling 2000 times, the bias, bias-corrected efficiency scores, standard deviation, and confidence interval can be obtained and are indicated in Table 6. Based on Table 6, some further discussions are described as follows. Note that the second column in Table 6 shows the BCC efficiency ($\hat{\phi}_j$) for the purpose of comparison.

The column 3 and column 4 in Table 6 display the bias of efficiency and bias-corrected technical efficiency, respectively. As shown in Table 6, the average bias for the 24 samples is -0.0879 in comparison with average BCC efficiency score, and the average bias-corrected technical efficiency score is 1.2223, indicating that the efficiency evaluated by BCC DEA model will be in general overestimated. In contrast with 8 DMUs are evaluated as technically efficient in BCC analysis, all of 24 firms will be inefficient after bias-correcting. Taking ASE as an example, the efficiency will be 1.1256 when bootstrapping while it is evaluated as efficient in BCC analysis. Note that, it is not necessary to keep the same efficiency ranking in bootstrap as in BCC model. For example, the technical efficiencies of Stack Devices and TICP are respectively 1 and 1.007 in BCC DEA analysis, while their efficiencies become 1.1268 and 1.0799 after the bias-correcting. The analysis reveals that, neglecting the bias will generally lead to the different results from that with consideration of bootstrapping bias.

The efficiencies estimated by BDEA method for each DMU construct a distribution, rather than a deterministic value in DEA analysis. Based on the results of resampling 2000 times, the 90% confidence interval of each firm can be obtained and displayed in Table 6 (column 6 and 7). For example, the bias-corrected efficiency score of ASE is 1.1256 and the 90% confidence interval would be from 1.0055 to 1.3249 with standard deviation of 0.0082. At the aggregate level, the average bias-corrected efficiency of 24 firms would be 1.2223, implying that taking all 24 samples as a whole it should expand output by 22.23 percent or 3.3 billion US dollars while keeping all inputs unchanged, so as to achieve efficient. For comparison, the output shortages of24 firms based on BCC and BDEA are indicated in Table 7, from which one can see that, the efficiency will be overestimated, and output shortage will be underestimated in BCC analysis.

Table 5. The results of traditional DEA analysis

DMU	Firm	CRSTE	VRSTE	SE	Scale economy
1	ASE	1.002	1.000	0.998	DRS
2	Amkor	1.000	1.000	1.000	CRS
3	SPIL	1.354	1.149	0.849	DRS
4	Stats ChipPAC	1.217	1.093	0.898	DRS
5	Powertech	1.000	1.000	1.000	CRS
6	ChipMOS	1.583	1.438	0.908	DRS
7	Jiangsu Changjiang	1.297	1.136	0.876	DRS
8	Chipbond	1.266	1.115	0.881	DRS
9	STS	1.000	1.000	1.000	CRS
10	Formosa Advanced	1.264	1.233	0.975	DRS
11	King Yuan	1.347	1.169	0.868	DRS
12	Unisem	1.000	1.000	1.000	CRS
13	Greatek	1.245	1.176	0.945	DRS
14	Walton Advanced	1.393	1.310	0.940	DRS
15	AOI	1.231	1.219	0.990	IRS
16	Nantong Fujitsu	1.587	1.457	0.918	DRS
17	OSE	1.389	1.354	0.975	DRS
18	Lingsen	1.237	1.234	0.998	DRS
19	Sigurd	1.193	1.189	0.997	IRS
20	Tong Hsing	1.087	1.007	0.926	IRS
21	TICP	1.058	1.008	0.953	IRS
22	Stack Devices	1.092	1.000	0.916	IRS
23	Aptos	1.092	1.000	0.916	IRS
24	Xintec	1.000	1.000	1.000	CRS
	mean	1.206	1.134	0.947	

Note: CRSTE, VRSTE stand for technical efficiency under assumption of CRS, VRS, respectively, SE denotes scale efficiency

Table 6. The result of bootstrap DEA

Firm	$\hat{\phi}_j$	Bias	Bias- corrected	S.D.	Confidence	Interval
					5%	95%
ASE	1.0000	-0.1256	1.1256	0.0082	1.0055	1.3249
Amkor	1.0000	-0.1219	1.1219	0.0075	1.0042	1.3077
SPIL	1.1613	-0.0785	1.2398	0.0023	1.1665	1.3497
Stats ChipPAC	1.0957	-0.0620	1.1577	0.0014	1.1024	1.2472
Powertech	1.0000	-0.0839	1.0838	0.0027	1.0061	1.2082
ChipMOS	1.3757	-0.0679	1.4436	0.0012	1.3835	1.5185
Jiangsu Changjiang	1.1463	-0.0545	1.2008	0.0007	1.1520	1.2618
Chipbond	1.1249	-0.0484	1.1733	0.0005	1.1294	1.2207
STS	1.0000	-0.1239	1.1239	0.0079	1.0056	1.3226
Formosa Advanced	1.2576	-0.0785	1.3361	0.0015	1.2642	1.4122
King Yuan	1.1819	-0.0505	1.2323	0.0006	1.1873	1.2847
Unisem	1.0000	-0.1241	1.1241	0.0078	1.0055	1.3243
Greatek	1.1904	-0.0730	1.2634	0.0013	1.1956	1.3335
Walton Advanced	1.3566	-0.0840	1.4406	0.0024	1.3643	1.5422
AOI	1.1857	-0.0815	1.2672	0.0022	1.1923	1.3678
Nantong Fujitsu	1.5227	-0.0975	1.6202	0.0030	1.5292	1.7381
OSE	1.3757	-0.0899	1.4656	0.0023	1.3813	1.5603
Lingsen	1.2311	-0.0839	1.3150	0.0028	1.2377	1.4305
Sigurd	1.0096	-0.0713	1.0809	0.0029	1.0121	1.2075
Tong Hsing	1.0040	-0.0666	1.0706	0.0015	1.0094	1.1578
TICP	1.0070	-0.0729	1.0799	0.0019	1.0131	1.1767
Stack Devices	1.0000	-0.1268	1.1268	0.0079	1.0067	1.3259
Aptos	1.0000	-0.1235	1.1230	0.0077	1.0054	1.3186
Xintec	1.0000	-0.1199	1.1199	0.0061	1.0044	1.2616
Mean	1.1344	-0.0879	1.2223	0.0035	1.1402	1.3418

Table 7. output shortage for 24 companies based on different models

Firm	BCC DEA		BCC BDEA	
	Shortage	%	Shortage	%
ASE	0	0	516.6	12.2
Amkor	0	0	362.9	12.3
SPIL	307.2	14.9	502.5	24.4
Stats ChipPAC	156.1	9.3	266.3	15.9
Powertech	0	0	106.1	8.4
ChipMOS	219.4	41.5	222.4	44.4
Jiangsu Changjiang	78.99.1	13.6	117.1	20.2
Chipbond	49.5	11.5	74.8	17.4
STS	0	0	61.4	12.3
Formosa Advanced	94.6	23.3	135.5	33.4
King Yuan	82.6	16.9	114.1	23.3
Unisem	0	0	56.5	12.3
Greatek	61.6	17.6	92.0	26.3
Walton Advanced	81.5	31.0	115.5	43.9
AOI	54.3	21.9	65.7	26.5
Nantong Fujitsu	126.1	45.7	171.4	62.1
OSE	133.5	35.4	175.3	46.5
Lingsen	51.2	23.4	68.9	31.5
Sigurd	30.2	18.9	13.0	8.1
Tong Hsing	1.5	0.7	14.2	6.8
TICP	1.2	0.8	12.0	7.9
Stack Devices	0	0	8.5	12.5
Aptos	0	0	11.5	12.4
Xintec	0	0	22.2	11.9
Total	1529.5		3306	
mean	95.6		137.8	

Note: unit in the column of shortage is in million US dollars

5. CONCLUDING REMARKS

Due to quick recovery of the global economy and substantial growth of smart phones, and other portable electronic devices, the output value of world's ICPT reached 47 billion U.S. dollars in the year of 2010; this means that the ICPT plays an important role in the supply chain of electronic devices. As such, the operating efficiency for ICPT worldwide firms deserves in-depth investigation. In this paper we evaluate the technical and scale efficiencies for world's 24 ICPT firms. The empirical results indicate that, 8 DMUs including ASE, Amkor, Powertech, STS, Unisem, Stack Devices, Aptos, and Xintec are evaluated as technically efficient, based on the assumption of VRS. The mean technical efficiency of sampling DMUs is 1.134, implying that on average each of inefficient firm should expand their output (Gross sales) by 1.53 billion dollars, keeping all inputs unchanged so as to be efficient. Recently, outsourcing from such integrated device manufacturers as Intel, TI, Motolora, will be the good opportunity to increase their output for ICPT firms.

To investigate the effect of scale on efficiency, we further classify the sample into two categories in terms of total assets and by cluster analysis. The average technical efficiencies of larger and smaller groups are 1.048 and 1.160, respectively. The result of t-ratio test reveals that the null hypothesis of no efficiency difference cannot be accepted with 5% level of significance. We thus conclude that, on average the technical efficiency of larger firm is significantly higher than that of smaller one. The finding is in line with the fact of larger firms in general with competitive advantage due to scale effect.

As for the scale efficiency, the empirical results also show that, 5 firms, including Amkor, Powertech, STS, Unisem, Xintec, produce their output under optimal production scale. Of remaining companies, 13 (6) DMUs exhibit DRS (IRS), indicating that it is necessary to adjust production scale for these 19 companies so as to be scale efficient.

Since the technical efficiencies are in general overestimated in traditional DEA models, we thus employ bootstrap DEA method proposed by Simar and Wilson [4]. The results indicate that none of sampling DMU is evaluated as technically efficient and the average bias-corrected efficiency is 1.2223 which is obviously lower than those estimated by BCC model. Taking ASE as an example, it is evaluated as efficient based on BCC model, while its bias-corrected efficiency becomes 1.1256 when using BDEA method due to the existence of bias.

Since the ICPT is a high-tech industry, in addition to scale effect, there may be some other factors such as R&D expenses, the number of patents owned by each firm, which may also significantly influence firms' technical efficiency, thus investigating the possible influencing factors, including internal and external, deserves to further research. Moreover, as we mentioned earlier the ICPT companies generally consist of two production divisions, namely packaging and testing, each division in fact produces its production by using different technologies; therefore one of possible avenues for future study is to evaluate performance for ICPT industry by using Network DEA models

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COMPETING INTERESTS

Author has declared that no competing interests exist.

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