Asian Journal of Economic Modelling
ISSN(e): 2312-3656
ISSN(p): 2313-2884
DOI: 10.18488/journal.8.2018.62.191.202
Vol. 6, No. 2, 191-202

URL: www.aessweb.com

TWO-STAGE PERFORMANCE EVALUATION OF DOMESTIC AND FOREIGN BANKS IN TAIWAN

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ABSTRACT

This paper provides an integration of independent component analysis and network slacks-based measure for performance analysis for foreign and domestic banks in Taiwan Independent component analysis was used to reduce data dimensionality of variables for a more discerning data envelopment analysis (DEA) performance evaluation. The authors then adopted performance evaluation structure based on a two-stage network model using network slacks-based measure: the production efficiency and the profitability efficiency. This study showed that domestic banks were more efficient than foreign banks in operational performance and production efficiency. The empirical results of the proposed ICA-NSBM model may be used to improve the discriminative ability of the performance evaluation using DEA methodology.

Article History
Received: 16 March 2018
Revised: 17 April 2018
Accepted: 20 April 2018
Published: 24 April 2018

Keywords
Two-stage performance
Evaluation
Independent component analysis
Network slacks-based measure
Domestic banks
Foreign banks
Data envelopment analysis

JEL Classification:
D61, M21.

Contribution/ Originality: This study contributes to the existing literature by comparing the operation performance, in terms of production and profit efficiency, between domestic and foreign banks in Taiwan. It observed that domestic banks had benefited from economies of scale as well as economies of scope and performed better.

1. INTRODUCTION

There has been a number of studies on the prevalence of data envelopment analysis (DEA) following the research of (Charnes *et al.*, 1978). In recent years, researchers have identified differences between single-stage and multi-stage analysis in banking efficiency analysis (Ho and Wu, 2009; Lo and Lu, 2009; Hsiao *et al.*, 2010; Avkiran, 2011; Paradi *et al.*, 2011). Issues arise from multi-stage efficiency analysis have also drawn much attention in recent literature (Cook *et al.*, 2010). For instance, Seiford and Zhu (1999) used a two-stage production performance measurement for the U.S. commercial banking system for its profitability and marketability efficiencies. They found there was a differential preference in banking at the operational scale, and by using this new approach, they can better identify new information on improved bank performance. Avkiran (2009) examined the use of network slacks-based measure (NSBM) to evaluate the profit efficiency of UAE banking. He pointed out that considering the divisional linkage within the organization, this innovative approach enabled management to identify profit centers' inefficiency. Kao and Hwang (2010) investigated the effect of network operational systems on performance measurement in the banking industry. They reported that more information regarding inefficiency sources could be obtained.

In light of previous researches, we postulated that evaluating multi-stage efficiency of multiple inputs and outputs would serve as managerial tool to pinpoint inefficiencies and potential improvements for maintaining sustainable competitive advantages. Several studies have attempted to tackle the discriminative power issue for the preferable efficiency analysis framework (Adler and Golany, 2001;2002; Adler and Yazhemsky, 2010). They deduced that the over-correlated relationship among input or output variables might result in bias of the efficiency measurement and in turn, could provide inappropriate feedback to the slack analysis. Adler and Yazhemsky (2010) explored the effect of principle component analysis (PCA) and variable reduction (VR) on performance evaluation in a simulation process. They demonstrated that PCA provided a more powerful and stable tool than VR in improving discrimination in DEA with minimal loss of observed information.

Independent component analysis (ICA), an extension of PCA, has been used as a feature selection to extract independent factors from a set of observed data without unveiling the mixing structure of unknown resources beforehand (Hyvärinen and Oja, 2000; Zheng *et al.*, 2006). It aims to remove the mutual information scheme form observed data with little to no discriminatory power, in order to improve the classification of efficient and inefficient decision-making units (DMUs). Kao *et al.* (2011) studied the ICA approach to further expand the application of DEA. They verified that ICA is another solution to the problem of variables correlation, using data of hospital industry to support the argument. To date, however, there is little literature available on banking performance measurement that integrates ICA with NSBM approach. Our research intends to supplement the literature on this particular issue, using data from the banking industry in Taiwan, and thus to produce a better measurement to evaluate performance of banks in Taiwan.

The purpose of this paper is to determine whether the proposed ICA-NSBM approach can effectively evaluate performance with increased discriminative ability. We used data from Taiwan's domestic banking sector for the empirical analysis. We showed that the results obtained from this ICA-NSBM model provide sufficient information on efficiency, which can then be used to improve performance and supervision direction for the management. In addition, the results of our model are both robust and significant. We asserted that this ICA-NSBM approach is superior to the one without transformation of variables in the NSBM model. Findings in this paper are useful to those who are responsible for performance evaluation in the field of DEA publications.

The rest of the paper is structured as follows: Section 2 introduces the framework of bank performance model. Section 3 presents a review of data for our empirical work. The methodology applied to construct the proposed banking performance model are demonstrated in Section 4. Section 5 reports the empirical results. Finally, Section 6 offers the conclusions.

2. BANK PERFORMANCE EVALUATION FRAMEWORK

Most of the previous studies have adopted DEA analysis for performance evaluation using in the banking industry (Berger and Humphey, 1997; Seiford and Zhu, 1999; Cooper *et al.*, 2000; Luo, 2003; Fethi and Pasiouras, 2010). Since the organizational structure has rapidly expanded in accordance with efficiency direction, a single performance evaluation may not serve aggressive management insight well. As such, researches on multi-stage performance evaluation structure have emerged (Ho and Wu, 2009; Lo and Lu, 2009; Avkiran, 2011; Paradi *et al.*, 2011). This paper adopted the two-stage performance evaluation structure, which is composed of the production efficiency and the profitability efficiency measurements, to assess the operational performance of domestic and foreign banks in Taiwan, as shown in Fig. 1.

The production efficiency evaluation was done in the first stage of the operational performance model and the profitability efficiency evaluation in the second stage, respectively. In the stage of production efficiency evaluation, the model followed a production approach used in previous literature that aimed to measure whether banks utilize input resources to generate relevant outputs as financial service. Fixed assets, operating expense, and equity were defined as specific inputs for production efficiency measurement. For the output variables selection, deposits and loans were used as intermediate outputs from the first stage. Keep in mind that if deposits and loans cannot be effectively exercised, these financial service capacities may not maximize the profit of the bank. The input-output variables used to assess the profitability efficiency evaluation reflected bank managers' objective of profit maximization, which depended on the financial service capacities in the phase of production. Three variables used were: interest revenue, fee revenue, and profit as final output variables for profitability efficiency evaluation. the full definition of input, intermediate, and output variables selected for the two-stage performance evaluation in this paper was described in Table 1.

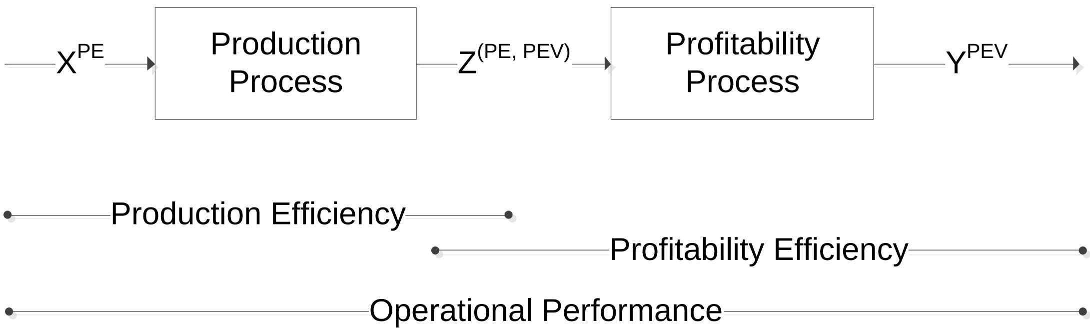

Fig-1. Two-stage performance evaluation of Taiwan foreign bank
Source: Evaluation structure developed by us according to the review of literatures

Table-1. Definition and explanation of variables

	Variables	**Definition and explanation**
Inputs	Fixed assets	Any tangible and intangible assets that are capable of being owned or controlled by company's year-end
	Operating expenses	The sum of a business's operating expenses for a specific year
	Equity	The value of an ownership interest in property, including shareholders' equity in a business
Intermediate inputs/outputs	Deposits	It is recorded as a liability for the bank, representing the amount owed by the bank to the customer for a specific year.
	Loans	Loans are recorded by the amount of outstanding principal, with unearned income excluded.
Outputs	Interest revenue	The interest earned by a company during the period indicated in the heading of the income statement under the accrual method.
	Fee revenue	It is mainly derived from service and penalty charges and, to a much lesser extent, from asset sales and property leasing. Examples are deposit and transaction fees.
	Profit	The residual income of a firm after adding total revenue and gains and subtracting all expenses and losses for the reporting period

Source: The definition of selected variables developed by us according to the review of literatures

3. DATA

We chose sample of banking industry in Taiwan from domestic and foreign banks for the period between 2011 and 2014, whose operations are regulated by Taiwan Financial Supervisory Commission. The data were taken from annual reports published by banks and the Taiwan Economic Journal (TEJ) database (Lo and Lu, 2009) which provided in-depth and abundant information available to the public. Banks with incomplete data were eventually left out of this study. We examined 30 domestic and 17 foreign banks in total.

Table 2 presented the descriptive statistics of our sample data for empirical evaluation analysis. From this table, we can see that the variable values of domestic banks were quite higher than foreign banks across various sizes of operation. Though there were not many foreign financial institutions in Taiwan, financial reforms, an open policy of the establishment of the financial institution and the implementation of Economic Corporation Framework Agreement (ECFA) between Taiwan and China in recent years have gradually attracted foreign banks into Taiwan's banking market; they hoped to adapt to Chinese culture in preparation for future business opportunities in China.

According to Lo and Lu (2009) , there was a positive correlation between input and output variables under the basic assumption of DEA evaluation analysis. The correlation matrix for all variables was illustrated in Table 3. Table 3 demonstrated that there were significant positive correlation relationships among all of these selected variables. Note that the correlations between fee revenue and deposits and loans were relatively low. This could represent a potential opportunity for bank managers to develop aggressive strategy to survive a competitive environment. Yet Kao *et al.* (2011) pointed out the shortcoming of DEA evaluation analysis: high correlation between input or output variables may affect the weight of variables, thus skewed the results of performance evaluation. They proposed the ICA approach to comb through input variables for independent signals before applying DEA. Following this ICA approach, in our model, we also extended it to intermediate and output variables selections for the two-stage structure of performance evaluation before building the NSMB model.

Table-2. Descriptive statistics

Variable	All sample				Domestic		Foreign	
	Mean	**Std. Dev.**	**Maximum**	**Minimum**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Inputs								
Fixed assets	8,683	13,849	76,575	1	13,542	15,383	107	285
Operating expense	3,513	4,058	15,578	27	5,320	4,087	325	385
Equity	38,834	52,010	245,473	340	59,543	55,343	2,290	1,694
Intermediates								
Deposits	537,103	709,384	3,185,433	357	830,682	742,583	19,023	22,875
Loans	412,469	542,574	2,079,133	1,274	631,145	574,272	26,570	27,047
Outputs								
Interest revenue	10,194	11,979	45,294	167	15,545	12,064	752	615
Fee Revenue	2,947	4,392	24,836	1	4,463	4,890	272	443
Profit	3,699	4,714	17,895	2	5,486	5,090	548	622

Note: Monetary unit is million NT dollars.

Table-3. Correlation coefficients

Variables	Fixed assets	Operating expense	Equity	Deposits	Loans	Interest revenue	Fee Revenue	Profit
Fixed assets	1.00							
Operating expense	0.82	1.00						
Equity	0.91	0.91	1.00					
Deposits	0.94	0.91	0.96	1.00				
Loans	0.89	0.91	0.92	0.98	1.00			
Interest revenue	0.89	0.96	0.96	0.98	0.97	1.00		
Fee Revenue	0.52	0.79	0.65	0.55	0.50	0.65	1.00	
Profit	0.59	0.84	0.79	0.80	0.77	0.78	0.85	1.00

Source: : Table developed by us according to the results of SPSS22 software

4. METHOD

The methodology used in this paper for performance evaluation in banking industry was an integration of ICA with NSBM. ICA was first developed by Hyvärinen and Oja (2000) to reduce dimensionality of variables for a more discerning DEA performance evaluation. Since Tone and Tsutsui (2009) introduced NSBM, it was also used to construct the banking performance evaluation model with a two stages framework.

4.1. Independent Component Analysis

Independent component analysis (ICA), an extension of principle component analysis (PCA), is a useful statistical technique that aims to transform observed variables into independent components (ICs) as linear combinations of underlying latent variables. However, its intention is slightly different from PCA. PCA tries to find out unobserved principle components (PCs) that maximize the variance of the estimated. These independent components are assumed to be non-Gaussian and mutually independent. While the typical ICA model has been widely demonstrated in cases of blind signal separation (BSS) and feature selection in various researches (Shi *et al.*, 2006; Zheng *et al.*, 2006) there have still been few applications in DEA publications. A literature closely related ICA-DEA model was developed and published in the *European Journal of Operational Research.*

Following Kao *et al.* (2011) we derived the independent input, intermediate, and output variables using ICA technique. The ICA technique presented here was developed in Hyvärinen and Oja (2000). Assume that n observed variables denoted by x_j, $j=1,2,\ldots,n$ as a combination of n independent, non-Gaussian and unknown latent sources s_i, $i=1,2,\ldots,n$. That is,

$$x_j = \alpha_{j1}s_1 + \alpha_{j2}s_2 + \ldots + \alpha_{jn}s_n, \qquad (1)$$

Given these assumptions, the typical ICA model of observed variables matrix X can be written as Hyvärinen *et al.* (2001):

$$\mathrm{X} = \mathrm{AS} = \sum_{i=1}^{n} \alpha_i s_i \qquad (2)$$

Where A is an unknown mixing matrix and S is a statistically independent latent variables matrix that cannot be directly measured from the observed variable matrix X. The objective of ICA is to estimate the independent component matrix S and the unknown mixing matrix A by finding a de-mixing matrix W. Substituting estimated W for A, the equation can be rewritten as:

$$\mathrm{V} = [v_i] = \mathrm{S} = \mathrm{WX} = \mathrm{A}^{-1}\mathrm{X} \qquad (3)$$

The de-mixing matrix W is applied to transform the observed matrix X to generate the corresponding ICs, such that we can obtain an estimation of V in which the vectors are statistically independent. These vectors are called independent components (ICs). ICs can then be used to estimate the latent variables s_i.

4.2. Network Slacks-Based Measure

Tone and Tsutsui (2009) developed the network slacks-based measure (NSBM) model to deal with intermediate measures directly in a single evaluation procedure. Therefore, we used the NSBM model to evaluate the operational performance of domestic and foreign banks in Taiwan, where the production efficiency and the profitability efficiency evaluation with some linkages. This paper adopted the non-oriented, variable return to scale of the NSBM for bank performance model, where n DMUs (banks) $(j=1,2,\ldots,n)$ consist of K operation stages $(k=1,2,\ldots,K)$. Let m_k and r_k be the number of inputs and outputs to stage k, respectively. In addition, let

(k,h) denote the link leading from stage k to stage h and let $s^{k-}(s^{k+})$ denote the input (output) slacks to stage k. The objective function of operational performance evaluation, ρ^{NSBM}, can be defined as follows (Tone and Tsutsui, 2009):

$$\rho^{NSBM} = \min \frac{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s^{k-}}{x_{io}^k}\right)\right]}{\sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s^{k+}}{y_{ro}^k}\right)\right]} \quad (4)$$

Subject to:

$$\sum_{j=1}^{n} \lambda^{PE} X^{PE} = X^{PE} - S^{PE-}, \quad (4.1)$$

$$\sum_{j=1}^{n} \lambda^{PE} Z^{(PE,PEV)} = \sum_{j=1}^{n} \lambda^{PEV} Z^{(PE,PEV)} \quad (4.2)$$

$$\sum_{j=1}^{n} \lambda^{PE} = 1\ ;\ \lambda^{PE}, S^{PE-} \geq 0 \quad (4.3)$$

$$\sum_{j=1}^{n} \lambda^{PEV} Y^{PEV} = Y^{PEV} + S^{PEV+} \quad (4.4)$$

$$\sum_{j=1}^{n} \lambda^{PEV} = 1\ ;\ \lambda^{PEV}, S^{PEV-} \geq 0 \quad (4.5)$$

$$w_{PE} + w_{PEV} = 1,\ \ w_k \geq 0 \quad (4.6)$$

For the free linking constraints (4.2) we assumed that the output of the previous stage was the same as the following stage input. Moreover, since w_k is a user-specified weight for each stages, specific contribution of each stage on the operational performance can be identified. we assumed that both the weights of the production efficiency and the profitability efficiency stages were 0.5. In addition to the operational performance measurement, Tone and Tsutsui (2009) also defined the objective function of stage efficiency as follows:

$$\rho_k^{NSBM} = \frac{1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{io}^k}\right)}{1 - \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_r^{k+*}}{y_{ro}^k}\right)} \quad (5)$$

Where s^{k-*} and s^{k+*} were the optimal input and output slacks for equation (4).

We used the NSBM model to measure the operational performance as well as the efficiency of stages. The results can provide more managerial improvement insights.

5. EMPIRICAL RESULTS AND ANALYSIS

5.1 Efficiency Analysis Using NSBM Model

The operational performance of banking industry in Taiwan based on the non-oriented NSBM model, proposed by Tone and Tsutsui (2009) was summarized in Table 4. As can be shown in the table, the highest average score for the profitability efficiency in the three partitions of sample (all, domestic only, and foreign only) were 0.653, 0.818 and 0.677, respectively. These findings suggested that the bank managers' pursuit of profitability might still be in vain. The average score of production efficiency was 0.703 in the sub-sample of domestic banks, suggesting domestic banks were still trying to find more efficient ways of using assets and/or saving resource. However, this NSBM model simply measured performance with input, intermediate, and output variables without considering the correlated relationship between input and/or output variables. The discriminatory power of the NSBM model (for further evaluation purposes) may also suffer from the correlation problem.

Table-4. Summarized results of the NSBM model

	Operational performance	Production efficiency	Profitability efficiency
All sample			
Mean	0.624	0.488	0.653
Std. Dev.	0.145	0.186	0.156
Domestic			
Mean	0.800	0.703	0.818
Std. Dev.	0.168	0.226	0.185
Foreign			
Mean	0.654	0.596	0.677
Std. Dev.	0.142	0.175	0.171

Source: Table developed by us according to the results of DEA-Solver Pro14 software

5.2. Efficiency Analysis Using ICA-NSBM Model

Unlike the general NSBM model mention above, the preliminary analysis showed significant correlation among variables, which implied the existence of hidden information. Using the ICA technique, we derived independent components for the input, intermediate, and output variables. We then proceed to build the NSBM performance model. Tables 5-7 summarize the information with which was used to select important ICs for input, intermediate, and output variables for the production efficiency and the profitability efficiency in the following NSBM model.

Initially, there were three original input variables and two output variables for evaluating the production efficiency among banks. Adopting the ICA technique to estimate the independent component using a de-mixing matrix ($\mathbf{W}$), , the characteristic of maximization of non-Gaussianity was the criterion for choosing the important ICs (Hyvärinen, 1999). We chose variables with kurtosis values of IC_1^{PE}, IC_3^{PE}, $IC_2^{(PE,PEV)}$, IC_1^{PEV} and IC_3^{PE} greater than 3 for the production and the profitability efficiency evaluation.

Table-5. The Kurtosis and de-mixing matrix ($\mathbf{W}$) corresponding to the ICs for inputs in production efficiency

Variables	IC_1^{PE}	IC_2^{PE}	IC_3^{PE}
Fixed assets	0.000161	0.000135	-0.000057
Operating expense	-0.000076	0.000380	-0.000020
Equity	-0.000030	-0.000440	0.000026
Kurtosis value	**12.26204**	-0.40707	**3.20801**

Source: Table developed by us according to the results of MATLAB software

Table-6. The Kurtosis and de-mixing matrix ($\mathbf{W}$) corresponding to the ICs for intermediate outputs in production efficiency

Variables	$IC_1^{(PE,PEV)}$	$IC_2^{(PE,PEV)}$
Deposits	-0.000008	0.000010
Loans	-0.000001	0.000003
Kurtosis value	-0.28694	**5.19957**

Source: Table developed by us according to the results of MATLAB software

Table-7. The Kurtosis and de-mixing matrix ($\mathbf{W}$) corresponding to the ICs for outputs in profitability efficiency

Variables	IC_1^{PEV}	IC_2^{PEV}	IC_3^{PEV}
Interest revenue	0.000009	-0.000404	0.000224
Fee revenue	0.000104	0.000138	-0.000442
Profit	0.000088	-0.000085	0.000048
Kurtosis value	**7.8914**	1.3154	**3.5402**

Source: Table developed by us according to the results of MATLAB software

Table 8 and Table 9 summarized the ICA-NSBM model results. The NSBM score was the weighted sum of the performance score from this two-stage evaluation. An operational performance score equal to unity suggested efficient production and profitability, while a value less than 1 indicating inefficiency. Detailed operational performance scores and ranking from the ICA-NSBM model were shown in Table 8. Note that there were 7 banks, 4 of domestic and 3 of foreign banks, which outperformed and better-ranked than other banks. There were 17 banks, 10 of domestic and 7 of foreign banks, which ranked top 1 in production efficiency. 11 banks, 5 of domestic and 6 of foreign, ranked top 1 in the profitability efficiency. From Table 8, for those with less than 1 score value, it suggested the managers should try new profit maximization plans as soon as possible. The average overall, the efficiency score of banking industry in Taiwan was only a mediocre 0.559, while the production efficiency score was relatively good.

We used Wilcoxon signed-rank test to demonstrate whether the proposed ICA-NSBM model was significantly different from the NSBM model in evaluating banking operating performance from Table 10, the Z--values of the two-tailed Wilcoxon signed-rank test for the difference between the ICA-NSBM and NSBM models, we can conclude that our ICA-NSBM model was significantly different than NSBM model. With further discussion on discriminatory power of the two models (Section 5.3), we then argued that ICA-NSBM was a better model than NSBM model.

5.3. Banking Performance Management Matrix

The managerial matrix was generated by combining the results of the production efficiency and the profitability efficiency. Using the matrix, it was easy find the benchmark banks as to provide some guidance to improve operational performance, as shown in Fig. 2. This matrix can be divided into four groups with respect to their relative production efficiency (horizontal) of and profitability efficiency (vertical) from the ICA-NSBM model. The segmented lines were the mean production score (0.745) and the mean profitability score (0.520), respectively. From the information of this matrix, combining with results shown in Table 8, we suggested all Taiwan banks should pay more attention to their resource allocation, and to identify their own competitive advantages. Furthermore, Figure 2 also the different distributions of corporate-consumer efficiencies obtained from the ICA-NSBM and NSBM models were also illustrated in Figure 2. The results showed that the proposed ICA-NSBM model yields better discriminatory power than the NSBM model.

Table-8. The results of ICA-NSBM for domestic and foreign banks in Taiwan

DMU	Operational		Production efficiency		Profitability efficiency	
	Score	Rank	Score	Rank	Score	Rank
Domestic						
1	1	1	1	1	1	1
2	0.462	29	1	1	0.301	34
3	0.597	23	1	1	0.402	27
4	0.639	22	0.7988	25	0.519	21
5	0.663	20	0.7945	26	0.537	19
6	0.656	21	0.6729	32	0.548	16
7	1	1	1	1	1	1
8	1	1	1	1	1	1
9	0.893	8	0.6414	33	1	1
10	0.283	40	0.8124	23	0.177	43
11	0.669	18	1	1	0.503	23
12	0.228	42	0.1976	45	0.236	36
13	0.280	41	0.5137	38	0.195	42
14	0.541	25	0.8914	20	0.389	28
15	0.292	39	0.575	36	0.204	41
16	0.152	44	0.6811	31	0.091	45
17	0.338	35	0.7014	29	0.221	38
18	0.672	17	0.801	24	0.545	17
19	0.824	9	1	1	0.700	14
20	0.540	26	1	1	0.370	29
21	0.586	24	0.7378	28	0.463	26
22	0.816	10	0.5539	37	0.762	12
23	0.438	31	0.6872	30	0.331	31
24	0.442	30	0.4792	39	0.369	30
25	0.674	16	0.8734	21	0.544	18
26	1	1	1	1	1	1
27	0.351	34	1	1	0.213	40
28	0.700	13	0.5861	35	0.718	13
29	0.354	33	0.818	22	0.231	37
30	0.321	37	0.4431	41	0.255	35
Foreign						
31	0.678	15	1	1	0.513	22
32	0.723	12	1	1	0.566	15
33	0.479	27	1	1	0.315	32
34	1	1	1	1	1	1
35	0.808	11	0.6171	34	1	1
36	0.062	45	0.02	47	1	1
37	1	1	1	1	1	1
38	0.696	14	0.4622	40	1	1
39	1	1	1	1	1	1
40	0.025	47	0.0631	46	0.020	46
41	0.413	32	0.3655	42	0.475	25
42	0.025	46	1	1	0.013	47
43	0.305	38	0.2121	44	0.523	20
44	0.665	19	1	1	0.498	24
45	0.195	43	0.2576	43	0.169	44
46	0.464	28	1	1	0.302	33
47	0.333	36	0.7403	27	0.214	39

Source: Table developed by us according to the results of DEA-Solver Pro14 software

Table-9. The summarized results of ICA-NSBM model

	Operational performance	Production efficiency	Profitability efficiency
All sample			
Mean	0.559	0.745	0.520
Std. Dev.	0.282	0.283	0.315
Domestic			
Mean	0.626	0.874	0.529
Std. Dev.	0.241	0.148	0.293
Foreign			
Mean	0.576	0.696	0.638
Std. Dev.	0.363	0.373	0.383

Source: Table developed by us according to the results of DEA-Solver Pro14 software

Table-10. Wilcoxon signed-rank test between ICA-NSBM model and NSBM model

Models	Period	NSBM		
		Operating performance	Production efficiency	Profitability efficiency
ICA-NSBM	2010	4.429 (0.000)	0.531(0.603)	3.754 (0.000)

Source: Table developed by us according to the results of DEA-Solver Pro14 software

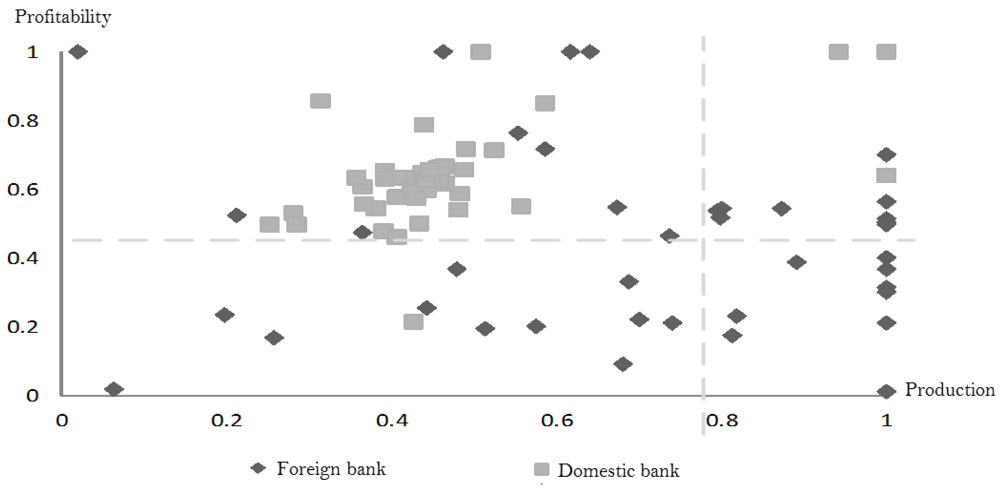

Fig-2. The banking performance management matrix

Source: Figure developed by us according to the results of DEA-Solver Pro14 software

5. CONCLUSION

This paper incorporated the concepts of variable preprocess and intermediate output for the performance evaluation analysis, and has therefore applied the ICA-NSBM model to assess the operational performance, composited of production efficiency and profitability efficiency, of domestic and foreign banks in Taiwan.

The empirical results were summarized as follow. (1) Domestic banks have a performed better than the foreign banks in the overall operational performance and the production efficiency score, while foreign banks performed better in the profitability efficiency dimension. The difference could be attributed to that domestic banks had benefited from scale, fund asset, and intermediate function, while the foreign banks had focused on specific service functions like wealth management and fund allocation for senior clients. (2) The proposed ICA-NSBM model showed higher standard deviation and was significantly different from the NSBM model; it provided several useful managerial insights.

We formulated the operational performance of banking industry in this paper based on two-stage evaluation structure consisting of production efficiency and profitability efficiency. Further extension of this paper could focus on the weight of sub-structural evaluation by using analytic network process (AHP). It would render significant parameters on DEA analysis valuable to practical application. Furthermore, the structure of performance evaluation needs to take into account more precise dimensions and variable selection such as uncontrollable and environment variables.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.
Contributors/Acknowledgement: Both authors contributed equally to the conception and design of the study.

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