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Using independent component analysis and network DEA to improve bank performance evaluation

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ABSTRACT

Given the importance of accurate performance evaluation for the banking industry, this paper uses data on Taiwanese domestic banks and investigates whether it is useful to construct an integrated performance model in order to address the problems of efficiency-analysis with the aid of an independent component analysis (ICA) and a network slacks-based measure (NSBM). ICA is related to the search for latent information; in it, independent components (ICs) from the observed data and selected statistically unrelated ICs are used as new input, intermediate, and output variables for the NSBM. The NSBM is then used in the investigation of multiple-dimension efficiencies, along with operating performance, in the Taiwanese domestic banking sector. The results show that the proposed ICA-NSBM model provides sufficient information to determine the main sources of inefficiency at the dimensional level and demonstrates excellent significant discriminative capability.

1. Introduction

Efficient measurement plays a crucial role for achieving sustainable development in the competitive environment (Amado et al., 2012). Therefore, understanding the performance level of homogeneous industry may help managers and regulators for generating better management strategies and industrial policies. The aim of this paper is to propose an enhanced performance evaluation framework based on the integration of network data envelopment analysis (NDEA) and independent component analysis (ICA) for more accurate operational performance evaluation, in which we try to encapsulate the four dimensions of performance as production, corporate banking, consumer banking, and profitability. Under the ongoing Economic Cooperation Framework Agreement (ECFA) negotiation between Taiwan and China, the Taiwanese domestic commercial banks will expect to obtain permission to provide financial services in China. This movement motivated this paper to use the Taiwanese domestic banking sector for the application of our proposed comprehensive methodology. For the current proposal, we seek to provide meaningfully managerial information for the selected decision making units (DMU), as emphasizing which dimension outperforms and identifying the inefficient sources of each dimension, which can contribute to the formulation of strategic plans and the upgrade of service quality for possible challenge.

Unlike classical DEA models, NDEA not only can do for modeling an organization but also for measuring the performance of its components (Färe and Grosskopf, 2000). NDEA has great potential for practical application, to provide valuable information to management (Avkiran, 2009). Owing to its advantage of generalizability, NDEA has been widely applied in industries such as banking (Avkiran, 2009; Kao and Hwang, 2010), tourism (Hsieh and Lin, 2010), major league baseball (Lewis and Sexton, 2004), and airport (Yu, 2010). Kao and Hwang (2010) investigated the effect of network operational systems on performance measurement in the banking industry. They reported that more information regarding sources of inefficiency could be obtained using this method than using other methods. With the introduction of a slack-based approach for NDEA, the so-called network slacks-based measure (NSBM) model, by Tone and Tsutsui (2009), much attention has also been devoted to the complex internal operations required for performance evaluation (Avkiran, 2009; Yu, 2010). Avkiran (2009) examined the use of NSBM to evaluate the profit efficiency of banking in the United Arab Emirates. He pointed out that considering divisional linkage within an organization, this innovative approach enabled management to identify inefficiency in three profit centers (e.g., loans, advances, and overdrafts (LAO), mortgaged real estate loans (MREL), and discounted commercial bills (DCB)). Among the many measurement applications for which NSBM can be utilized may be identifying inefficiencies and potential for improvement in the effort to maintain a sustainable competitive advantage.

In light of the foregoing, one problem in the development of a performance evaluation methodology using DEA is the discriminative validity of the performance with regard to the presence of large dimensionality in inputs or outputs (Bian, 2012; Jenkins and Anderson, 2003). Evaluating observations with a misspecified model may lead to the identification of an inappropriate efficient frontier and therefore to a loss of discriminability. Therefore, ensuring the quality of the DEA model is of crucial importance (Pedraja-Chaparro et al., 1999). Several studies have looked at the

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improvement of the discriminatory power of the efficiency-analysis framework (Adler and Golany, 2001, 2002; Adler and Yazhemsky, 2010; Kao et al., 2011). They deduced that several variable selection methods were incorporated for enhancing performance discrimination without requiring additional preferential information. 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 was a more powerful, more stable tool than VR in terms of the improvement of discrimination in DEA, with minimal loss of observed information.

ICA is a feature-selection technique, an extension of PCA, that has been applied to extract independent factors from a set of observed data when the mixing structure of unknown resources is not already known (Hyvärinen and Oja, 2000). ICA aims to remove the mutual information scheme from observed data that have little or no discriminatory power in order to improve the classification of efficient and inefficient DMUs. Kao et al. (2011) verified that ICA stands beside PCA in terms of effectiveness as a solution to the discrimination problem of the DEA model, by using it in efficiency measurement for hospitals. To date, however, the existing ICA-DEA approach discusses only ICA components as input features of the DEA model, and there is little or no literature available on banking performance measurement that integrates ICA with NSBM approaches.

The contributions of this study are as follows. First, the proposed ICA-NSBM model is used to provide a detailed performance analysis of the Taiwanese domestic banking sector in 2009. The decomposition of operational performance into production, intermediate services, and profitability efficiencies done here is an important addition to the current literature on bank efficiency. Second, we estimate and compare bank efficiency as obtained from a multi-stage network structure, using the ICA-NSBM and NSBM models. This comparison will show that the NSBM model may provide misleading results for the measurement of large and/or highly correlated inputs/outputs, whereas the proposed ICA-NSBM model may enhance the discriminatory power of efficiency measurement.

The rest of the paper is structured as follows. Section 2 introduces the proposed model for measuring the operational performance of the Taiwanese domestic banking sector. In Section 3, the tools—variable dimension reduction performed via the ICA process and performance evaluation using NSBM—are introduced. Section 4 presents a review of data from our empirical work. Section 5 discusses these empirical results. Finally, Section 6 offers conclusions.

2. The conceptual framework of bank performance

The main purpose of this paper is to model performance evaluation of bank operations with the application of Network DEA framework. In addition to the four-dimensional network operation structure from the related literature, considering the role of non-performing loans (i.e. bad loan) in the lending process is also important for performance management.

2.1. The operational performance model

Performance evaluation can be treated as a monitor and benchmark tool by which a manager of a firm estimates its operational activity, surveys whether its objective is achieved, finds the market position of homogeneous industry, and further provides an improvement direction if a firm has inefficient performance. How to evaluate performance and demonstrate the discriminative ability of measures, therefore, becomes an important issue in organization. Referring to the relevant studies of banking performance measurement, one of the widely applied analytical methods is DEA (Ho and Wu, 2009). Conventionally the performance evaluation of banking operations is based on one stage production model (Banker et al., 1984; Charnes et al., 1978; Färe and Lovell, 1978). However, as pointed out by Paradi et al. (2011), the operational system of banking is too complicated for the DEA evaluation framework. For example, banking offers a broad choice of financial services and products in numerous transaction channels to varied customers including private individuals, small and midsized enterprises, and large corporations. Consequently, the actual sources of value creation of banking services cannot be seen if the performance evaluation approach is still adopted by DEA. An increasing number of studies show that it is more meaningful to decompose organizational performance into sub-dimensions (Avkiran, 2009; Lo and Lu, 2009; Seiford and Zhu, 1999; Tsutsui and Goto, 2009). Following this concept, the bank operational activity in this paper can be defined as a production process made up of network structure, in which sun-dimensions have sequential and parallel relationship. It is simply assumed that the bank uses a set of resources to provide financial services to the varied customers for making a profit. However, this is still a simplified conceptual framework that does not incorporate dynamic management into consideration.

This network structure for performance evaluation in banking has been considered in this paper. This paper adopted a four-dimensional performance evaluation model for Taiwanese domestic banking based on three related literatures: first, the NDEA model by a slack-based measure approach, namely NSBM model proposed by Tone and Tsutsui (2009), for decomposing the overall performance into several sun-dimensional performances with stressing the importance of slacks to performance management. Second, the contribution made by Avkiran (2009) is used with respect to the role played by profit center in financial service delivery and profit generation process. Finally, Barros et al. (2012), which quantify the impact of non-performing loans (NPLs) on bank performance, underpin the inclusion of NPLs in the performance model. Our proposed evaluation framework for Taiwanese domestic banking operational performance can be separated into four main dimensions: production, corporate banking, consumer banking, and profitability, as depicted in Fig. 1. Corporate and consumer banking could integrate into service efficiency. It can provide a comprehensive evaluation of banking performance, allowing managers to identify major sources of and opportunities to improve it.

2.2. Variable selection

To measure the operational performance of Taiwanese domestic banking, a four-dimensional network performance structure via NSBM model is built. Since the results of performance measurement are determined by the selected input, intermediate, and output variables, we chose variables for our proposed model on the basis of a review of the abundant existing literature on banking performance (Drake et al., 2006; Fukuyama and Matousek, 2011; Lo and Lu, 2009; Luo, 2003). Specifically, in the dimension of production, a bank utilizes a set of resources (e.g. capital, fixed assets and employee) into trying to provide financial products and services that will attract customers from deposits acquirement and loans lending as intermediate outputs. This paper used three inputs, fixed assets, operating expenses, and equity, and two intermediate outputs, deposits and loans, to measure the production efficiency. In the service dimension, we measured the ability to recover loans in both corporate and consumer banking departments. We separated loans into corporate-banking loans and consumer-banking loans and used collection of both types of loans as intermediate-produced outputs to evaluate service efficiency. The allocation of loans was based on the loan quality statement from the banks' annual report supplement, which is a way of objectively assigning a proportion of the loans to the different subjects involved. Loan quality, which refers to non-performing loans as a proportion of total loans, is a credit analysis to determine a borrower's ability to repay loans and make loan decisions. In the profitability dimension, the input–output variables used to assess profitability efficiency reflect the managerial objective to maximize the bank's profit (Avkiran, 2006; Fama, 1980), which refers to the profit contribution made by lending services from corporate and customer-banking departments. We also used interest revenue,

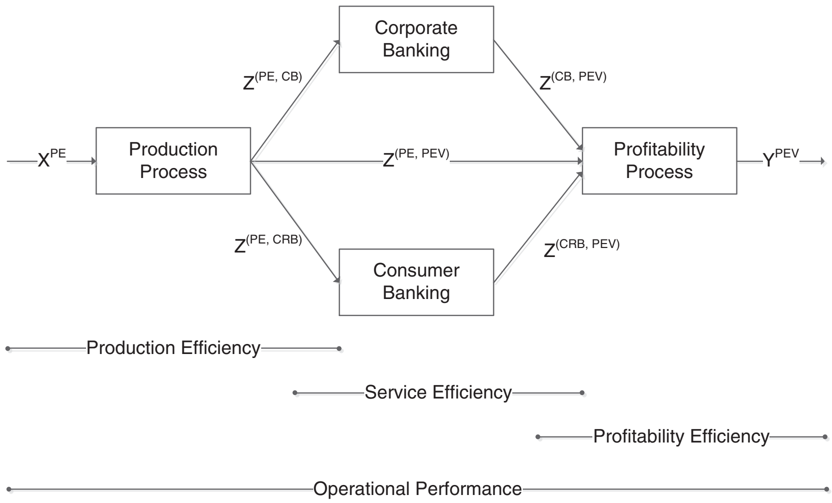

Fig. 1. Network structure of the Taiwanese domestic banks' operation system.

fee revenue, and profit as final outputs for the profitability evaluation. Table 1 defines the input, intermediate, and output variables selected for this study.

3. Methodology

To evaluate the effect of the proposed approach to performance evaluation, this paper constructed a specifically designed performance model that directly considered the intermediate linkage of individual dimensions within the organizational structure of Taiwanese banks. A combination of ICA and NSBM techniques was employed for the empirical analysis. First, ICA was applied to discover latent information about the observed variables and further improve the performance of the NSBM model. After the variables were preprocessed, the NSBM model was used to measure banks' operating performance in the sample period.

3.1. Independent component analysis

ICA is a useful statistical technique that aims to transform observed variables into independent components (ICs) in terms of a linear combination of underlying latent variables. These independent components are assumed to be non-Gaussian and mutually independent. While the typical ICA model has been widely demonstrated in the problem of blind signal separation (BSS) and feature selection in various academic studies (Shi et al., 2006; Zheng et al., 2006), there have also been a few applications using ICA in DEA publications.

The ICA technique presented here was originally developed in Hyvärinen and Oja (2000). Assume that n observed variables indicated by x_j, $j = 1,2,\ldots,n$ represent a combination of n independent, non-Gaussian, and unknown latent sources s_i, $i = 1,2,\ldots,n$,

$$x_j = \alpha_{j1}s_1 + \alpha_{j2}s_2 + \ldots + \alpha_{jn}s_n. \tag{1}$$

Given these assumptions, the typical ICA model of observed-variable matrix $\mathbf{X}$ can be written as follows (Hyvärinen et al., 2001):

$$\mathbf{X} = \mathbf{AS} = \sum_{i=1}^{n} \alpha_i s_i, \tag{2}$$

where $\mathbf{A}$ is an unknown mixing matrix and $\mathbf{S}$ is a statistically independent latent-variables matrix that cannot be directly measured from observed-variable matrix $\mathbf{X}$. The objective of the ICA model is to estimate the independent component matrix $\mathbf{S}$ and the unknown mixing matrix $\mathbf{A}$ based

Table 1
Definition and explanation of variables.

Variables	Definition and explanation
Production inputs	
Fixed assets	A long-term, tangible asset held for banks use and not expected to be converted to cash in the current or upcoming fiscal year.
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.
Loans recovery	This is a calculation that the exclusion of non-performing loans in the total amount of outstanding loans.
Profitability outputs	
Interest revenue	The interest earned by a bank 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. 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.

on a de-mixing matrix **W**. Substituting the estimated **W** for **A**, the equation can be rewritten as shown below.

$$\mathbf{V} = [\nu_i] = \mathbf{S} = \mathbf{WX} = \mathbf{A}^{-1}\mathbf{X} \tag{3}$$

Clearly, the de-mixing matrix **W** is applied to transform the observed matrix **X** to generate the corresponding ICs such that the vectors of **V** must be estimated to be as statistically independent as possible; these ICs are used to estimate and represent the latent variable s_i.

As mentioned above, we incorporate the ICA-DEA variable transformation developed by Kao et al. (2011) and further extend it for the NDEA structure. The independent components (ICs) are generated using the ICA approach to replace the original inputs/outputs with minimum loss of information, thereby reducing the dimensionality of the inputs/outputs for performance evaluation via NDEA. Kao et al. (2011) suggested that independent components with positive kurtosis values be selected as the candidate variables.

3.2. Network slacks-based measure

Tone and Tsutsui (2009) developed the NSBM model, which is not to be confused with a traditional DEA model since it can evaluate intermediate measures directly in a single procedure. Since bank production, provision of financial services, and profit generation are interdependent, it is important to evaluate dimensional efficiency to improve operational performance. Given this consideration, we used the non-oriented, variable return to scale of the NSBM model to evaluate bank operational performance and four dimensions (production, corporate banking, consumer banking, and profitability).

In this NSBM model, suppose there are n DMUs (Taiwan domestic banks) ($j = 1,2,\ldots,n$) consisting of K dimensions ($k = 1,2,\ldots,K$). Let m_k and r_k be the number of inputs and outputs for dimension k, respectively; and let us denote the intermediate link from dimension k to dimension h by $Z^{(k,h)}$ and the input (output) slacks to dimension K by S^{K-} (S^{K+}); the objective function of evaluating operational performance for the banking sector, ρ^{NSBM}, is defined as follows:

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

subject to:

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

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

$$\sum_{j=1}^{n} \lambda^{PE} Z^{(PE,CRB)} = \sum_{j=1}^{n} \lambda^{CRB} Z^{(PE,CRB)}, \tag{4.3}$$

$$\sum_{j=1}^{n} \lambda^{PE} Z^{(PE,PEV)} = \sum_{j=1}^{n} \lambda^{PEV} Z^{(PE,PEV)}, \tag{4.4}$$

$$\sum_{j=1}^{n} \lambda^{PE} = 1;\ \lambda^{PE}, S^{PE-} \geq 0, \tag{4.5}$$

$$\sum_{j=1}^{n} \lambda^{CB} Z^{(CB,PEV)} = \sum_{j=1}^{n} \lambda^{PEV} Z^{(CB,PEV)}, \tag{4.6}$$

$$\sum_{j=1}^{n} \lambda^{CB} = 1; \lambda^{CB}, S^{CB-} \geq 0, \tag{4.7}$$

$$\sum_{j=1}^{n} \lambda^{CRB} Z^{(CRB,PEV)} = \sum_{j=1}^{n} \lambda^{PEV} Z^{(CRB,PEV)}, \tag{4.8}$$

$$\sum_{j=1}^{n} \lambda^{CRB} = 1; \lambda^{CRB}, S^{CRB-} \geq 0, \tag{4.9}$$

$$\sum_{j=1}^{n} \lambda^{PEV} Y^{PEV} = Y^{PEV} + S^{PEV+}, \tag{4.10}$$

$$\sum_{j=1}^{n} \lambda^{PEV} = 1; \lambda^{PEV}, S^{PEV-} \geq 0, \tag{4.11}$$

$$w_{PE} + w_{CB} + w_{CRB} + w_{PEV} = 1, w_k \geq 0 \tag{4.12}$$

where the superscripts refer to dimension: *PE*, *CB*, *CRB*, and *PEV* symbolize the production dimension, the corporate service dimension, the consumer service dimension, and the profitability dimension, respectively. Meanwhile, (*PE*, *CB*), (*PE*, *CRB*) and (*PE*, *PEV*) represent the intermediate output from the production dimension to the corporate service, consumer service, and profitability dimensions, respectively. Finally, (CB, PEV) and (CRB, PEV) symbolize the intermediate output from the corporate and consumer banking service dimensions into the profitability dimension. With regard to these free-linking constraints (4.2)–(4.4), (4.6), and (4.8), we need to assume that the previous dimension's output is the same as the following dimension's input.

Next, λ^{PE}, λ^{CB}, λ^{CRB}, and λ^{PEV} are introduced as the intensity variables of each dimension for each DMU (bank), and w_{PE}, w_{CB}, w_{CRB}, and w_{PEV} are user-specified weights for each dimension; thus, we can observe their specific contributions to the operational performance of each bank. However, we presume that all dimensions are equally important to the operational activity of the bank. Tone and Tsutsui (2009) defined the objective function of dimensional efficiency as follows:

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

where S^{k-*} and S^{k+*} are the optimal input and output slacks for Eq. (4).

The efficiency of each dimension is measured by Eq. (5). The efficiency of production is subject to Eqs. (4.1)–(4.5); the efficiency of corporate banking is subject to Eqs. (4.6) and (4.7); the efficiency of consumer banking is subject to Eqs. (4.8) and (4.9); and the efficiency of profitability is subject to Eqs. (4.10) and (4.11).

Finally, we used the NSBM model to measure operational performance at the organizational level and the efficiency of the sub-dimensions. This is crucial in order to achieve the important task of providing specific managerial insights into how to achieve sufficient operational performance under the NBSM evaluation structure.

4. Data

We constructed our sample from the Taiwan Financial Supervisory Commission, considering all publicly quoted domestic banks in the database, which gave us a total of 39 banks for 2009. The sample dataset was used in the measurement of operating performance, which includes production efficiency, corporate service efficiency, consumer service efficiency, and profitability efficiency. All bank-specific data were obtained from the annual financial statistical abstract and annual report published by the Banking Bureau of the

Table 2
Descriptive statistics of variables.

Variables	Mean	Median	Minimum	Maximum	Std. dev.	Coef. var.
Production inputs						
Fixed assets	13,474	8275	1256	78,475	15,433	114.54
Operating expenses	8367	8336	584	25,974	6232	74.49
Equity	53,848	35,009	4140	236,452	52,169	96.88
Intermediate inputs/outputs						
Deposits	734,356	470,195	34,503	3,189,672	717,862	97.75
Loans	593,930	313,087	25,805	2,045,894	546,897	92.08
Loans recovery	565,503	282,559	26,047	2,043,020	549,592	97.19
Profitability outputs						
Interest revenue	8422	7126	449	22,659	6605	78.42
Fee revenue	2491	2251	27	6027	1815	72.86
Profit	1675	1008	19	10,664	3943	235.39

Note: All monetary units are in million NT dollars.

Financial Supervisory Commission and from individual bank reports. There were three criteria for exclusion from the sample: first, banks not included in the Financial Supervisory Commission's domestic bank database were excluded; as were, second, cases where bank-specific variables were not available (e.g., banks without an annual report); and third, if the bank-specific variable was zero or there was a missing or negative value, that bank was excluded. The final sample consists of 30 banks, for all of which complete data for 2009 were available.

Table 2 reveals the basic statistical characteristics of these banks. Three particularly noteworthy features emerge from these statistics. First, the variance of the selected variables is large (see the standard deviation column in the table) taking into consideration the various sizes of the sample banks. Second, the summary statistics provide an interesting context: profit accounted for approximately 10% of revenue (interest revenue plus fee revenue) at the sample mean. (Clearly, the largest domestic bank will show a ratio nearly 40% higher than this.) Finally, in terms of the well-known bad loan problems stemming from the subprime crisis in 2008, it is interesting to note that the non-performing loans ratio is around 4.79% at the sample mean for Taiwanese domestic banks. Hence, Taiwan may find it impossible to avoid liquidity risk unless there is a dramatic change in operating environment.

Table 3 demonstrates significant positive correlations among all selected variables via Pearson correlation matrix. Bian (2012) pointed out that DEA has a shortcoming due to large database dimensionality, in which there exist multiple correlations among the original inputs/outputs. That is, one of the reasons why an inefficient unit can be classified as efficient is that there may be redundant variables surrounding the efficiency frontier (Cinca and Molinero, 2004). Kao et al. (2011) proposed the ICA approach to process input variables for independent components before conducting DEA. It will help to choose a subset

Table 4
Summarized results of the NSBM model.

	Performance dimensions				
	Operational performance	Production	Corporate banking	Consumer banking	Profitability
Mean	0.811	0.782	0.848	0.818	0.815
Std. dev.	0.124	0.222	0.161	0.151	0.158
Max	1.000	1.000	1.000	1.000	1.000
Min	0.586	0.377	0.466	0.552	0.416
Efficient DMUs	5	11	8	8	7
	(16.7)[a]	(36.7)	(26.7)	(26.7)	(23.3)

Note: [a] the numbers in the parentheses are the corresponding the percentage of efficient DMU of sample.

of variables that provide the majority of information contained with the original variables. Therefore, the ICA approach was also adopted in this paper. We not only deal with the input variables but also extend our analysis to intermediate and output variables for the network structure of performance evaluation before using the NSMB model.

5. Empirical results and analysis

5.1. Efficiency analysis using NSBM model

The comprehensive efficiency analysis in the non-oriented NSBM model proposed by Tone and Tsutsui (2009) is presented in Table 4. As can be seen from the table, only five banks are identified as efficient (a unity efficiency score in overall operational performance; operational performance is the weighted sum of the score for all dimensions of efficiency with internal linkages. On the other hand, inefficient banks have an efficiency score of less than one even if they have a unity efficiency score in certain dimensions. The average score for production efficiency is 0.782 and higher standard deviation of production efficiency exists within the scope of these performance criteria. These findings suggest that although the maximum number of efficient DMUs is achieved, the worse production efficiency can hamper operational performance and that some inefficient DMUs may be trying to find more efficient ways utilizing assets and saving resources.

However, this NSBM model simply measures performance with input, intermediate, and output variables, without using the ICA approach for a preprocessed variables procedure. The discriminatory power of the NSBM model may also be inadequate for further evaluation purposes.

5.2. Efficiency analysis using the ICA-NSBM model

Unlike the general NSBM model, the significant correlation of homogeneous variables in the ICA-NSBM model reflects some hidden information; therefore, we first apply the ICA approach to find the independent components, which represent the statistically independent input, intermediate, and output variables. We then build the

Table 3
Correlation coefficients between variables.

	Fixed assets	Operating expenses	Equity	Deposits	Loans	Loans recovery	Interest revenue	Fee revenue	Profit
Fixed assets	1								
Operating expenses	0.75	1							
Equity	0.92	0.83	1						
Deposits	0.92	0.78	0.94	1					
Loans	0.83	0.76	0.89	0.93	1				
Loans recovery	0.81	0.87	0.93	0.92	0.94	1			
Interest revenue	0.73	0.93	0.87	0.84	0.87	0.97	1		
Fee revenue	0.60	0.84	0.78	0.68	0.65	0.81	0.84	1	
Profit	0.60	0.56	0.76	0.76	0.75	0.79	0.73	0.64	1

Note: all coefficients are statistically significant at the 1% level.

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

Variables	$IC_1^{PE(I)}$	$IC_2^{PE(I)}$	$IC_3^{PE(I)}$
Fixed assets	0.0000672220	0.0001357821	−0.0000224256
Operating expense	−0.0001744409	0.0000679143	−0.0002295118
Equity	0.0000121884	−0.0000513388	0.0000166993
Kurtosis value	12.23793	9.21914	2.52652

NSBM performance model. Tables 5 and 6 summarize information relevant to the selection of important ICs as input and output variables for production efficiency in the NSBM model. There are three original input variables and two output variables for evaluating production efficiency for these banking data. After applying the ICA approach to estimate the independent component using a de-mixing matrix (W), the criterion of maximal non-Gaussianity is used to choose important ICs (Kao et al., 2011). The kurtosis values of $IC_1^{PE(I)}$, $IC_2^{PE(I)}$ and $IC_1^{PE(O)}$, as input and output variables for production efficiency evaluation, are more than 3.

Finally, the operational performance and sub-dimensional efficiency of the banks under the ICA-NSBM model are obtained, as shown in Table 7. Operational performance falls between 1.000 and 0.183, and average efficiency score is 0.535, implying that there is still room for improvement. Regarding production efficiency, 10 domestic banks are efficient; the average efficiency score is 0.890. The results reveal that very few domestic banks provide financial service capacity inefficiently. It is worth noticing that the average scores for corporate and consumer banking efficiency are 0.471 and 0.307, indicating that inefficient DMUs must handle the possibility of loss from debtor default, a fact which has not previously been considered. Ways to handle this might include, for example, securing a loan with collateral, which will help disperse credit risk usefully. Therefore, improvements in these two dimensions are more important for inefficient banks. Banking managers may be able to quickly execute new business plans that take this information into account. In addition, compared to the results of the NSBM model in Table 4, Taiwanese domestic banks show a wide distribution of all performance scores obtained from the ICA-NSBM model and sown in Table 7. The results reveal that the proposed ICA-NSBM model may provide better discriminatory power than does the NSBM model.

5.3. Slack analysis of ICA-NSBM model

According to Cooper et al. (2000), DEA not only provides an efficiency score for performance ranking but also identifies inefficient DMUs and sources of inefficiency, which provide valuable information for performance management. That is why DEA has become a popular managerial tool in academic and professional practice. However, it is interesting to find that the slacks for dimensional-level inputs and outputs indicate some inefficient sources that are not normally visible with the general DEA model. Consequently, we move the focus of the analysis to potential improvements to inefficient DMUs or sub-DMUs. The results of slack analysis of the ICA-NSBM model in production efficiency need to be retransformed to allow useful resource management. The retransformed procedure for input and output slacks is adapted from Kao et al. (2011) as Eq. (6):

$$\begin{aligned}
&\mathit{Minimize}\ \varepsilon_1+\varepsilon_2\\
&\mathit{Subject\ to}\ \le \varepsilon_1\left|\Delta IC_1^{PE(I)}-0.0000672220\Delta x_1^{PE}+0.0001744409\Delta x_2^{PE}\right.\\
&\qquad\qquad\left.-0.0000121884\Delta x_3^{PE}\right|\\
&\qquad\qquad\left|\Delta IC_2^{PE(I)}-0.0001357821\Delta x_1^{PE}-0.0000679143\Delta x_2^{PE}\right.\\
&\qquad\qquad\left.+0.0000513388\Delta x_3^{PE}\right|\le\varepsilon_2,\\
&x_i^{PE}\rho_{ij}x_j^{PE}\, i=1,2,3; j=1,2,3;\\
&\Delta x_i^{PE}\in \mathit{Integer}\ \ i=1,2,3;
\end{aligned}\tag{6}$$

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

Variables	$IC_1^{PE(O)}$	$IC_2^{PE(O)}$
Deposits	0.0000036301	−0.0000005012
Loans	−0.0000041405	0.0000024481
Kurtosis value	5.15870	−0.08819

Table 7
ICA-NSBM model for banking in 2009.

DMU	Performance dimensions				
	Operational performance	Production	Corporate banking	Consumer banking	Profitability
1	0.837	1.000	1.000	0.346	1.000
2	1.000	1.000	1.000	1.000	1.000
3	1.000	1.000	1.000	1.000	1.000
4	1.000	1.000	1.000	1.000	1.000
5	0.669	0.716	0.863	0.110	0.747
6	0.582	0.883	0.514	0.112	0.604
7	0.202	0.443	0.147	0.103	0.176
8	0.464	0.693	0.392	0.192	0.416
9	0.410	0.577	0.281	0.163	0.413
10	0.256	0.977	0.207	0.040	0.641
11	0.807	0.693	0.995	0.153	0.601
12	0.183	0.986	0.127	0.028	0.649
13	0.219	0.984	0.168	0.034	0.648
14	0.367	0.987	0.227	0.102	0.618
15	0.771	1.000	0.504	0.929	0.877
16	0.883	1.000	0.686	0.929	0.993
17	0.370	0.933	0.145	0.213	0.814
18	0.332	0.845	0.195	0.112	0.523
19	0.354	0.845	0.256	0.088	0.756
20	0.504	0.742	0.335	0.326	0.467
21	0.420	0.834	0.232	0.159	0.476
22	0.252	1.000	0.130	0.063	0.724
23	0.340	0.870	0.223	0.118	0.447
24	0.277	1.000	0.162	0.071	0.612
25	0.287	0.888	0.194	0.054	0.609
26	0.945	0.894	0.975	0.499	1.000
27	0.777	1.000	0.812	0.252	0.944
28	0.995	1.000	1.000	0.938	1.000
29	0.323	0.951	0.211	0.062	0.708
30	0.220	0.967	0.160	0.030	0.671
Mean	0.535	0.890	0.471	0.307	0.704
Std. dev.	0.289	0.144	0.350	0.351	0.222
Max	1.000	1.000	1.000	1.000	1.000
Min	0.183	0.443	0.127	0.028	0.176
Efficient DMU	3 (10.0)[a]	10 (33.3)	5 (16.7)	3 (10.0)	6 (20.0)

Note: [a] the numbers in the parentheses are corresponding to the percentage of efficient DMU of sample.

Table 8
Slack analysis of the proposed ICA-NSBM model using DMU_6 as an example.

Variables	Original value	Models	
		NSBM	ICA-NSBM
Production efficiency inputs			
Fixed assets	24,243	320	558
Operating expenses	11,690	N/A	269
Equity	79,154	N/A	1899
Intermediate outputs			
Deposits	1,211,387	118,050	37,597
Loans	1,011,068	102,214	40,867
DMU_6 performance score		0.768	0.883

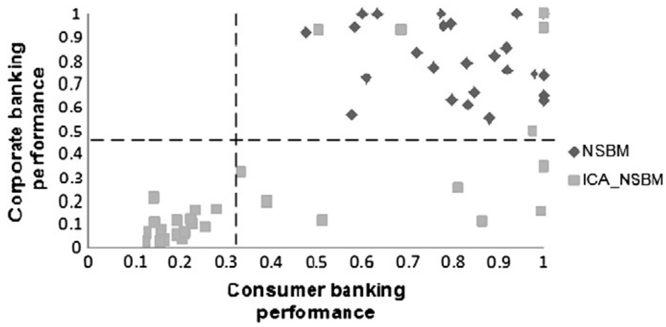

Fig. 2. The corporate-consumer banking performance matrix.

$$\begin{aligned}&\textit{Minimize}\ \varepsilon_3\\&\textit{Subject to}\ \left|\Delta IC_1^{PE(O)}-0.0000036301\Delta y_1^{PE}+0.0000041405\Delta y_2^{PE}\right|\le\varepsilon_3,\\&y_i^{PE}=\rho_{ij}y_j^{PE}i=1,2;j=1,2;\\&\Delta y_i^{PE}\in Integer\ \ i=1,2;\end{aligned} \tag{7}$$

where x_i^{PE} or x_j^{PE} are the original inputs for production efficiency, ρ_{ij} is the correlation coefficient between input variables x_i^{PE} and x_j^{PE}, y_i^{PE} or y_j^{PE} are the original outputs for production efficiency, ρ_{rs} is the correlation coefficient between y_i^{PE} and y_j^{PE}; ΔIC_i is the slack generated by the ICA-NSBM model, Δx_i^{PE} is the retransformed input slack adjustment of the ICA-NSBM model, and Δy_i^{PE} is the retransformed output slack adjustment of the ICA-NSBM model.

The third column of Table 8 suggests that, compared with an efficient DMU, the various inputs in the inefficient banks are excessive and the outputs fall short. The slack analysis suggests that banks' resources are adequately reallocated to achieve the best frontier—in other words, the efficient one. For example, to make bank production efficient, DMU_6 can set fixed assets, operating expenses, and equity appropriately for next year by cutting them down by 558, 269, and 1899 million, respectively. DMU_6 can also provide a favorable interest rate for deposits and deregulate credit policy for loans by adding 37,597 and 40,867 million. This indicates that it is best to attract a larger number of corporate and individual clients to fully utilize financial service capacity, and that this DMU also needs to reallocate resources. Thus, a slack analysis can investigate the utilization of input, intermediate, and output variables to improve the production efficiency of inefficient banks.

5.4. Corporate–consumer banking performance matrix

The ICA-NBSM framework is applied to the simultaneous evaluation of operational performance with multiple-dimensional efficiency, which also provides a good opportunity to get further insight into efficiency emphasis in each dimension. Since we divided service efficiency into corporate and consumer service efficiency, it is easy to verify which banks observed inefficiencies and in which dimension, and further, to provide direction for improvement priorities. All banks are located according to their corporate and consumer efficiency expressed as two criteria constituting the corporate–consumer banking performance matrix, as shown in Fig. 2. The performance matrix classifies each bank into a quadrant in terms of two criteria: (1) whether the performance score of the corporate banking dimension is more or less than the mean score (0.471); (2) whether the performance score of the consumer banking service is more or less than the mean score (0.307), serving as the vertical and horizontal axes, respectively. There is a notable difference between the service efficiency of domestic banks, as some banks have high corporate and consumer banking efficiency both; others have low corporate and consumer banking efficiency; the banking manager or regulator should pay attention to this phenomenon. The performance matrix supplies valuable information on how to improve dimensional performance, which is a help for operational performance. In addition, Fig. 2 also shows the comparison of distribution of bank performance obtained from the ICA-NSBM and NSBM models. The results reveal that the proposed ICA-NSBM model yields better discriminatory power than the NSBM model.

5.5. Robustness revaluation

To evaluate the robustness of the proposed ICA-NSBM model for banking performance measurement, the results of the NSBM model and the proposed model were tested using the same evaluation structure at different sample horizons, in order to validate whether the ICA-NSBM model has better discriminatory power than the NSBM model. In this section, the years 2007 and 2008 are considered. The evaluation results are summarized in Table 9 for the two criteria of efficiency score and standard deviation. Table 9 indicates that the proposed ICA-NSBM model outperforms the other performance model at all stages under both sample periods. Based on this finding, the proposed ICA-NSBM model for banking performance measurement, with its better discriminatory capability, should be able to facilitate good judgment in determining potential competitive power for all banks. It can be concluded, therefore, that the proposed ICA-NSBM model is likely to be effective for general application.

5.6. Significance test

In order to demonstrate whether the proposed ICA-NSBM model is significantly superior to the NSBM model in evaluating bank's operating performance, the Wilcoxon signed-rank test is applied. This is a commonly adopted approach for determining whether there is a statistically significant difference between the results of two different models (Zhang, 2001). The test has a well-known characteristic: it does not require that a limiting data-distribution structure be pre-specified, and deals with the signs and ranks of the values in relation to the mean value of the objective model. This study employs the Wilcoxon test to estimate the evaluating performance of the two proposed models under different sample horizons. Table 10 presents the Z-statistic values of the two-tailed Wilcoxon signed-rank test for the difference between the ICA-NSBM and NSBM models. Under both sample periods, the proposed ICA-NSBM model is significantly different from the proposed NSBM model; the profitability stage of the year 2008 and the production stage of the year 2007 are mere exceptions. We can therefore conclude that the proposed model is significantly better than the NSBM model

Table 9
Robustness evaluation of NSBM and ICA-NSBM model by different sample horizons.

Sample period	Models	Operational performance		Production		Corporate banking		Consumer banking		Profitability	
		Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
2007	NSBM	0.824	0.131	0.900	0.123	0.871	0.146	0.758	0.180	0.767	0.195
	ICA-NSBM	0.546	0.247	0.856	0.197	0.628	0.337	0.247	0.339	0.891	0.161
2008	NSBM	0.885	0.093	0.916	0.108	0.910	0.132	0.854	0.144	0.850	0.153
	ICA-NSBM	0.411	0.252	0.345	0.330	0.314	0.346	0.446	0.280	0.870	0.193

Table 10
Wilcoxon signed-rank test between ICA-NSBM model and NSBM model under performance dimensions by different sample horizons.

Model	Sample period	NSBM				
		Performance dimensions				
		Operational performance	Production	Corporate banking	Consumer banking	Profitability
ICA-NSBM	2007	4.249***	0.713	3.346***	4.487***	3.111***
	2008	4.741***	4.469***	4.517***	4.292***	1.090
	2009	3.946***	1.918**	4.053***	4.530***	2.141***

Note: *** and ** indicate $p < 0.05$ and $p < 0.01$, respectively.

in evaluating operational performance and identifying the sources of inefficiencies.

6. Conclusion

This paper was designed to propose the innovative performance evaluation model to measure banking performance that is based on the NSBM model aided by ICA approach that is a variable-preprocessing tool. The operational performance is decomposed into four-dimensional performance by production, service, and profitability efficiencies. We can identify the contribution of each dimensional performance for organization. The proposed ICA-NSBM model is applied to provide a comprehensive analysis of the Taiwanese domestic banks in the research period in 2009. In addition, a general NSBM-based performance evaluation model is also built for the purposes of comparison to demonstrate the effectiveness of the proposed model using standard deviation and the Wilcoxon signed-rank test as criteria.

6.1. Managerial implications

This paper applies ICA-NSBM model and performance management matrix to evaluate and locate the operational performance of banks in Taiwanese banking industry in 2009. The main empirical results were summarized as two folds. First, the decomposition of operational performance into four components belonging to four dimensions provides a comprehensive analysis on Taiwanese banking industry. It is worth noting that the performance of corporate and consumer banking was relatively uptight. Second, the proposed ICA-NSBM model can present higher standard deviations and more significant differences than the general NSBM model for obtaining the better discriminative ability of DEA-based performance framework and provide useful managerial insights.

In addition, the ICA-NSBM as proposed in this paper provides several managerial insights. Firstly, we can find out that the performance of corporate and consumer banking services, in average, indicated from 0.307 to 0.471. It is implied that domestic banks have first priority to adjust risk policy avoiding the probability of non-performing loans increases. In addition, the average operational performance of Taiwanese domestic banks is 0.535, which could be attributed to over-competition phenomenon. Moreover, this paper exhibits the operating position of corporate and consumer banking services of banks that contributes to if the bank wants to improve their service performance, which direction and benchmark it needs to improve priority. Finally, we may encourage that Mergers and Acquisition (M&A) activity will facilitate the development of Taiwanese banking because there is a significant difference in operating scale between evaluated domestic banks.

6.2. Comparison with other studies

This paper integrated the ICA approach with the NSBM model to propose an enhanced network DEA-based performance evaluation model of banking industry. The proposed ICA-NSBM model is different from the recent development of network DEA-based performance evaluation model in the banking industry (Assaf et al., 2011; Avkiran, 2009). Recently, other studies improving discrimination ability of DEA framework using PCA (Adler and Yazhemsky, 2010) and ICA (Kao et al., 2011) have been examined. Therefore, as can be seen in the previous literature, the variable selection approach employed by this paper may help to enhance the performance evaluation accuracy of network DEA-based model for evaluating banking performance. In addition, the current paper emphasizes building an enhanced performance evaluation for four-dimension for providing much useful information to performance management.

6.3. Research limitation and future research

However, there still exist some limitations to the proposed model, which may render it impractical. The current study assumes that the weights for efficiency in all dimensions are equal, an assumption that might not correspond to the real situation and therefore limits the generalizability of our findings. The analytic network process (ANP) technique, therefore, could be an effective solution by making pair-wise comparisons of dimensions from an interview and questionnaire with the experts. On the other hand, the ICA-NSBM model applied in this paper is still a simplified evaluation structure without taking the concept of dynamic evaluation, undesired variables, and environmental factors into consideration. Therefore, future research for further extension of performance evaluation framework may provide a room for enriching its contribution in practice. This research takes a step toward developing an effective approach for integrating ICA into NSBM to enhance the discriminative ability of performance evaluation via DEA framework. In addition, there is a critical need for empirical research into efficiency performance evaluation, so that an effective approach to promoting performance evaluation can be precisely identified.

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