Identifying Bank Failures with Two-stage Data Envelopment Analysis in the Worst-case Scenario: The Case of Taiwan Banks

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Abstract: - In the banking industry, the production process can be described as a two-stage process. There are a number of published data envelopment analysis (DEA) papers that study the bank performance with two-stage model. However, none of them is applied to identify bank failure. In fact, only one of them deals with negative profit data. In the real world, failed banks or firms often produced negative profit for several years before they went into bankruptcy. To fit this situation this paper introduces a two-stage worst-practice frontier DEA (WPF-DEA) model that can deal with negative profit data and effectively identify failed bank(s) in the worse-case scenario. This model is applied in an empirical study. The result is then compared with the result from a two-stage best-practice frontier DEA model to show the adequacy of WPF-DEA model for identifying failed bank(s) in the worst-case scenario.

Key-Words: - Data envelopment analysis, two-stage, bankruptcy, worst-case scenario, worst-practice frontier.

1 Introduction

Data envelopment analysis (DEA), introduced by Charnes et al [1], is an approach for identifying best practices of peer decision making units (DMUs), in the presence of multiple inputs and outputs. In many cases, DMUs may also have intermediate measures.

In some countries such as Taiwan, the role played by the banks is primarily to mediate funds between depositors and borrowers. Based on this inter-mediation concept, the two-stage process of banking industry can be described as follows. In stage 1, banks collect deposits using their resources such as labor and physical capital. In stage 2, banks use their managerial expertise and marketing skills to transform the deposits into loans and investments. This two-stage production process is depicted in Figure 1.

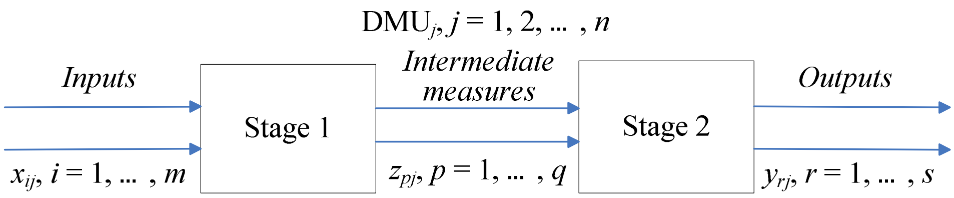

Figure 1. Illustration of the two-stage production process.

There are a number of authors utilizing DEA to describe this two-stage production process. Wang et al. [2] used DEA to study the effect of Information Technology on the performance of a firm. They developed a methodology to identify the efficiency of IT utilization and the importance of IT related activities and their effect on firm performance, within the two-stage DEA framework. Their methodology also evaluates the marginal benefits of IT. Seiford & Zhu [3] examined the performance of the top 55 U.S. commercial banks using a two-stage production process that separates profitability and marketability. They defined context-dependent performance measures for profitability and marketability which employ a DEA stratification model and a DEA attractiveness measure. The context-dependent performance measures combined with the original DEA measure can better characterize the profitability and marketability of 55 U.S. commercial banks. Zhu [4] again employed the two-stage production process that separates profitability and marketability for reconciling diverse measures which characterize the financial performance of the Fortune 500 companies. This study offers an alternative perspective and characterization on the performance of the Fortune

500 companies. Chen & Zhu [5] modified a two-stage BCC model that identifies the efficient frontier of a two-stage production process. A set of firms in the banking industry is used to illustrate how the new model can be utilized to (i) characterize the indirect impact of IT on firm performance, (ii) identify the efficient frontier of two principal value-added stages related to IT investment and profit generation, and (iii) highlight those firms that can be further analyzed for best practice benchmarking. Ho & Zhu [6] presented a study which uses a two-stage CCR model that separates efficiency and effectiveness to evaluate the performance of 41 listed corporations of the banking industry in Taiwan. The empirical result of this paper is that a company with better efficiency does not always mean that it has better effectiveness. Kao & Hwang [7] used a two-stage DEA model that separates profitability and marketability stages to measure managerial performance in 24 non-life insurance companies in Taiwan. In addition, this paper used Tobit regression model to examine factors that significantly influence managerial efficiency. Lo & Lu [8], employed a two-stage production process including profitability and marketability performance using DEA. They then combined the factor-specific measure and BCC model together not only to identify the inputs/outputs that are most important but also to distinguish those financial holding companies which can be treated a benchmarks. Kao & Hwang [9] modified the conventional DEA model by taking into account the series relationship of the two sub-processes within the whole process. Under this framework, the efficiency of the whole process can be decomposed into the product of the efficiencies of the two sub-processes. In addition, the case of Taiwanese non-life insurance companies showed that some unusual results which have appeared in the independent model do not exist in the relational model. The relational model developed in this paper is more reliable in measuring the efficiencies and consequently is capable of identifying the causes of inefficiency more accurately. Based on the structure of the model, the idea of efficiency decomposition can be extended to systems composed of multiple stages connected in series. Liang et al. [10] examined and extended two-stage DEA model using game theory concepts. Their resulting noncooperative and centralized approaches show that the overall efficiency of the two-stage process is a product of the efficiencies of the two individual stages. When there is only one intermediate measure connecting the two stages, both the noncooperative and centralized models yield the same results as applying the standard DEA model to the two stages separately. Liu & Wang [11] evaluated the overall efficiency of 17 Taiwanese printed circuit board manufacturing firms modelling the DMUs as a two-stage system. They divided the whole production process of the manufacturing firms into two sub-processes: production acquisition and profit earning. This study employs the relational two-stage DEA approach, which takes into account the series relationship of the two sub-processes within the whole process, to decompose and measure the efficiencies of the manufacturing firms. Chen et al. [12] developed an additive efficiency decomposition approach wherein the overall efficiency is expressed as a weighted sum of the efficiencies of the individual stages. This approach can be applied under both CRS and variable returns to scale (VRS) assumptions, which overcomes the limitation of the applicability to only constant returns to scale (CRS) situations for Kao & Hwang [9]. Liu [13] took the series relationship of the two individual stages into account in measuring the profitability and marketability efficiencies of the Taiwan financial holding companies. It is found that the low efficiency score of the whole process is mainly due to the low efficiency score of the marketability process. Decomposing the overall efficiency into the component efficiencies helps a company identify the stage that causes inefficiency. Finally, Zhu [14] measured airline performance using a two-stage process. In the first stage, resources such as fuel, salaries, and other factors are used to maintain the fleet size and load factor. In the second stage, the fleet size and load factors generate revenue. The model used is called the centralized efficiency model where two stages are used to optimize performance simultaneously. The approach generates efficiency decomposition for the two individual stages.

These published papers are summarized in Table 1 in terms of DEA models, country of study, and measures of inputs, intermediate and outputs. A recent review of two-stage DEA methods is given in the work of Cook et al. [15]. These studies use a two-stage production process linked by the same intermediate measures. However, none of them has been used to identify failed banks. Moreover, only one of them deals with negative profit data. In the real world, failed banks or firms often produced negative profit for several years before they went into bankruptcy.

Evaluating commercial banks' performance and monitoring their financial situation is of critical

Table 1. Two-stage DEA models applied in the banking or non-banking industry.

Author(s)	DEA model(s)	Country of study	Inputs	Intermediate measure(s)	Outputs
Wang, Gopal & Zionts [2]	BCC-I & modified BCC-I	U.S.A.	IT budget, fixed assets, employees	Deposits	Profits, fraction of loans recovered
Seiford & Zhu [3]	CCR-O, BCC-O, modified CCR-O & modified BCC-O	U.S.A.	Employees, assets, stockholders' equity	Revenues, profits	Market value, total return to investors, earning per share
Zhu [4]	CCR-I, BCC-I, modified CCR-I & modified BCC-I	U.S.A.	Employees, assets, stockholders' equity	Revenues, profits	Market value, total return to investors, earning per share
Chen & Zhu [5]	Modified BCC-I	U.S.A.	IT budget, fixed assets, employees	Deposits	Profits, fraction of loans recovered
Ho & Zhu [6]	CCR-O	Taiwan	Capital stocks, assets, branches, employees	Sales, deposits	Net income, interest income, non-interest income
Hwang & Kao [7]	Independent two-stage CCR-I	Taiwan	Business and administrative expenses, commissions and acquisition expenses	Direct written premiums, reinsurance premiums received	Net underwriting income, investment income
Lo & Lu [8]	Modified BCC-I & modified BCC-O	Taiwan	Assets, equity, employees	Revenue, profits	Earning per share, market value, stock price
Kao & Hwang [9]	Relational two-stage CCR	Taiwan	Operation expenses, insurance expenses	Direct written premiums, reinsurance premiums	Underwriting profit, investment profit
Liang, Cook, & Zhu [10]	Noncooperative and centralized two-stage CCR-I	First data set. U.S.A.	IT budget, fixed assets, employees	Deposits	Profits, fraction of loans recovered
		Second data set. U.S.A.	Employees, assets, stockholders' equity	Revenues, profits	Market value, total return to investors, earning per share
Liu & Wang [11]	Relational two-stage CCR-I	Taiwan			
Chen, Cook, Li, & Zhu [12]	Additive efficiency decomposition approach of two-stage CCR &BCC	Taiwan	Operation expenses, insurance expenses	Direct written premiums, reinsurance premiums	Underwriting profit, investment profit
Liu [13]	Additive efficiency decomposition approach of two-stage CCR	Taiwan	Employees, assets, equity	Profit, revenue	EPS, return, market value
Zhu [14]	Centralized two-stage CCR-I	U.S.A.	Cost per available seat mile, salaries per available seat mile, wages per available seat mile, benefit per	Load factor, fleet size	Revenue passenger miles, passenger revenue

available seat mile,
fuel expense
available seat mile

importance to stock holders, depositors, investors, and bank managers. Finding good performers as the target of investment is quite important; however, identifying bad performers as potentially failed banks deserves more attention. The reason is as follows. A type I error occurs if the borrowing venture or investment is bad and can't be identified in advance. The cost of a type I error is the loss resulting from a company defaulting on a loan or from a failed investment. The cost of a type II error is the loss represented by the revenue that the financial institutions or individual investors would have received if they had made the successful loan or investment. It is obvious that the cost of a type I error is much higher than that of a type II error. The identification or classification of credit or investment risk is therefore much more important.

However, we argue that the DEA models established in the most favorable scenario are not suitable for the purposes of identifying bad performers. The potential banks or corporations who will go out of business first usually are the ones of least competitiveness in comparison with others while the situations are getting less favorable. Especially, when they confront an economic depression or financial crisis such as the Asia financial crisis occurred in the year 1997 or the credit card and cash card crisis happened in Taiwan in the year 2005. The most recent case is the subprime mortgage financial crisis which started in the United States during the fall of 2006, caused several major financial corporations and hedge funds to shut down or file for bankruptcy, and spread to a global financial crisis recently. Therefore, we believe that it should be more meaningful to employ suitable model formulation for evaluating and ranking banks in the least favorable or worst-case scenario.

To fit in the least favorable or worst-case scenario, the concept of worst practice DEA was introduced but without fixed mathematical expression of model [16]. While the best practice DEA selects potentially distressed companies by measuring how inefficient they are in the most favorable scenario, the worst practice DEA picks out struggling companies based on how worst they perform in a worst-case scenario. The performance model results in placing the distressed firms on the worst-efficient frontier. This concept is a fit for the problem of credit or investment risk evaluation. Then a new trend of worst-practice frontier (WPF-DEA) models appeared in literature of DEA. Such published papers include [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], and [31]. The methodologies or models established in the above studies are based on the similar concept.

Therefore, the main purpose of this paper is to introduce a model formulation of WPF-DEA by incorporating the worst-practice frontier in two-stage DEA. The proposed model is able to deal with negative financial data which often result from the potential failed bank(s). The model is then applied in an empirical study in order to show that two-stage DEA model established in the worst-case scenario can effectively identify bank failures. The rest of this paper is organized as follows. The two-stage WPF-DEA model, which is established in the worst-case scenario, is discussed in the next section 2. In Section 3, the WPF-DEA model is applied in an empirical study of the bank failure happened in Taiwan. The result is compared with the result from a best-practice frontier DEA model to show the adequacy of WPF-DEA model for identifying failed bank(s) in the worst-case scenario. Finally, Section 4 gives the conclusion and future directions.

2 Methodology

DEA is a nonparametric linear programming approach designed specifically to measure relative efficiency in situations in which there are multiple inputs and outputs, and there is no obvious objective way of aggregating either inputs or outputs into a meaningful index of productive efficiency. No assumptions are made regarding the manner in which a decision-making unit (DMU) converts inputs into outputs. Traditional best-practice frontier DEA models establish a best-practice (efficient) frontier among the units based on a comparison process in which the ratio scales of the weighted sum of the outputs to that of the inputs are evaluated. The units on this frontier are efficient units, and the rest are deemed inefficient. The set of optimal weights for the DMU_o, the DMU to be evaluated, is actually the set of most favorable weights for the DMU_o in the sense that it maximizes the efficiency ratio scale. Therefore, traditional best-practice frontier DEA is considered to identify good (efficient) performers optimistically or in the most favorable scenario. Most of the DEA models and their applications in literature including those in

Table 1 are in the category of most favorable scenario. They focus on identifying the good (efficient) performers and therefore ranking all units according to the efficiency scores based on the best-practice frontier.

An important extension of the DEA model was developed by [32] as shown in model (1). Their model, unlike the original model, does not make the restrictive assumption of constant returns to scale. The property of translated invariance for BCC model, which was proved by [33], makes it useful to deal with negative data. For instance, if any output index r with negative values in the following input-oriented BCC model, all the values in index r, y_{rj} are translated to the new values $y_{rj} - p_r$. The constant p_r could be the most negative value so that the translated value, $y_{rj} - p_r$, become nonnegative for j = 1, 2, …, n. Translation of data does not alter the efficient frontier and the classification of DMUs as efficient or inefficient is invariant to translation.

$$\begin{aligned}
\min\ & \theta_o - \varepsilon\left(\sum\nolimits_{i=1}^{m} s_{io}^{-} + \sum\nolimits_{r=1}^{s} s_{ro}^{+}\right) \\
\text{s.t.}\ & x_{io}\theta_o - \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j - s_{io}^{-} = 0,\ \ i = 1,\cdots,m; \\
& \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j - s_{ro}^{+} = y_{ro},\ \ r = 1,\cdots,s; \\
& \sum\nolimits_{j=1}^{n} \lambda_j = 1; \\
& \lambda_j \ge 0,\ j = 1,\cdots,n;\ \ s_{io}^{-} \ge 0,\ i = 1,\cdots,m; \\
& s_{ro}^{+} \ge 0,\ r = 1,\cdots,s.
\end{aligned} \tag{1}$$

where ε is an non-Archimedean (infinitesimal) constant.

Throughout this study, we use input-oriented DEA model since the model yields scores and targets that are consistent with management objectives of improving the efficiencies of inputs such as employees and assets at the current levels of intermediate measures such as deposits in stage 1 and improving the efficiencies of intermediate measures at the current levels of outputs such as profits and fraction of loans recovered in stage 2.

Since the worst-practice frontier BCC (WPF-BCC) model has never been proposed formally, we hereby discuss the WPF-BCC model in a little more detail. We assume that there are n DMUs and the performance of each DMU, say DMU$_j$, is characterized by a production process of m inputs (x_{ij}, i = 1, …, m) to yield s outputs (y_{rj}, r = 1, …, s). To estimate the efficiency score of a specific DMU$_o$, the DMU to be evaluated, we solve

[WPF-BCC model]

$$\begin{aligned}
\max\ & \theta_o + \varepsilon\left(\sum\nolimits_{i=1}^{m} s_{io}^{+} + \sum\nolimits_{r=1}^{s} s_{ro}^{-}\right) \\
\text{s.t.}\ & x_{io}\theta_o - \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + s_{io}^{+} = 0,\ \ i = 1,\cdots,m; \\
& \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j + s_{ro}^{-} = y_{ro},\ \ r = 1,\cdots,s; \\
& \sum\nolimits_{j=1}^{n} \lambda_j = 1; \\
& \lambda_j \ge 0,\ j = 1,\cdots,n;\ \ s_{io}^{+} \ge 0,\ i = 1,\cdots,m; \\
& s_{ro}^{-} \ge 0,\ r = 1,\cdots,s.
\end{aligned} \tag{2}$$

Since the θ_o^* obtained as an optimal solution for (2) results in a set of least favorable weights for DMU$_o$ in the sense of minimizing the worst-efficiency ratio scale in an equivalent WPF-BCC fractional program model. The equivalent WPF-BCC fractional program obtained from (2) is:

$$\begin{aligned}
h_o = \min\ & \frac{\sum\nolimits_{r=1}^{s} u_r y_{ro} - u_o}{\sum\nolimits_{i=1}^{m} v_i x_{io}} \\
\text{s.t.}\ & \frac{\sum\nolimits_{r=1}^{s} u_r y_{rj} - u_o}{\sum\nolimits_{i=1}^{m} v_i x_{ij}} \ge 1,\ \ j = 1,\ldots,n; \\
& u_r \ge \varepsilon, r = 1,\cdots,s;\ v_i \ge \varepsilon, i = 1,\cdots,m;\ u_o \text{ free.}
\end{aligned} \tag{3}$$

Using (3), each DMU is assigned a set of least favorable weights. Therefore, WPF-BCC model can be considered as evaluating and ranking units in the worst-case (least favorable) scenario. The efficiency score obtained from the WPF-BCC model are considered as the worst efficiency. By virtue of the constraints in (2), the objective value θ_o^* is not less than 1. If an optimal solution obtained from the WPF-BCC model satisfies $\theta_o^* = 1$ and is zero-slack, then the DMU$_o$ is WPF-BCC worst efficient. The worst efficient units construct a worst-practice frontier.

To illustrate the difference between the best-practice frontier and the worst-practice frontier, we use an example of two inputs and one input data as shown in Table 2. All inputs are normalized to 1 for simplicity. The best-practice and worst-practice frontiers of the example are depicted in Figure 2.

Table 2. Illustrative data.

	DMU	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*
Input 1	x_1	4	7	8	4	1	4	6	3
Input 2	x_2	3	3	1	2	5	6	3	5
Output	y	1	1	1	1	1	1	1	1

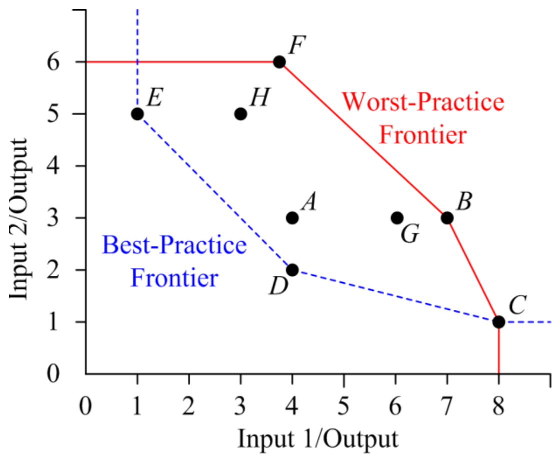

Figure 2. Illustration of the worst-practice frontier.

We now show that for WPF-BCC model, affine displacement (translation) of data does not alter the efficient frontier and the classification of DMUs as worst efficient or more efficient is invariant to translation. Therefore, we can adequately employ WPF-BCC model with translated data from negative profits. This is a very important advantage for empirical study since in the real world failed banks or firms often produced negative profit for several years before they went into bankruptcy.

Let the output measures y_{rj}, $r = 1, \ldots, s$, be displaced by p_r, $r = 1, \ldots, s$. Then the linear programming problem for the translated data is given by

$$\begin{aligned} \max\quad & \theta_o + \varepsilon\left(\sum_{i=1}^{m} s_{io}^{+} + \sum_{r=1}^{s} s_{ro}^{-}\right) \\ \text{s.t.}\quad & \bar{x}_{io}\theta_o - \sum_{j=1}^{n} \bar{x}_{ij}\lambda_j + s_{io}^{+} = 0, \quad i = 1,\cdots,m; \\ & \sum_{j=1}^{n} \bar{y}_{rj}\lambda_j + s_{ro}^{-} = \bar{y}_{ro}, \quad r = 1,\cdots,s; \\ & \sum_{j=1}^{n} \lambda_j = 1; \\ & \lambda_j \ge 0,\ j = 1,\cdots,n; \quad s_{io}^{+} \ge 0,\ i = 1,\cdots,m; \\ & s_{ro}^{-} \ge 0,\ r = 1,\cdots,s \end{aligned} \tag{4}$$

where $\bar{y}_{rj} = y_{rj} + p_r$ and $\bar{y}_{ro} = y_{ro} + p_r$.

Theorem. *For the WPF-BCC model*:

(a) *DMU_o is worst efficient for* (2) *if and only if DMU_o is worst efficient for* (4).

(b) *DMU_o is more efficient for* (2) *if and only if DMU_o is more efficient for* (4).

Proof. (a) When $\theta_o^* = 1$ and $s_{io}^{+} = s_{ro}^{-} = 0\ \forall i, r$, since $\sum_{j=1}^{n} \lambda_j = 1$, we have $\bar{y}_{ro} = y_{ro} + p_r$ and $\sum_{j=1}^{n} \bar{y}_{rj}\lambda_j = \sum_{j=1}^{n} y_{rj}\lambda_j + p_r$. Thus (2) and (4) are equivalent constraint sets.

(b) Statement (b) is logically equivalent to statement (a).

3 Empirical Study

3.1 Data

According to the Banking Law of the Republic of China (Taiwan), the primary functions of commercial banks include receiving checking account deposits and extending short term credit. The regular operations include servicing checking accounts, demands, and time deposits; extending short term and medium-term loans; engaging in domestic and foreign remittances and guaranty business; and underwriting government bonds, treasury bills, and corporate bonds. From Banking Law of Taiwan, one can find the detailed operations in which a commercial bank may engage. From looking at the operation contents of the commercial banks in Taiwan, one soon realizes that the availability of funds and the costs of deposits are not the major considerations of banks. The emphasis of bank management is to make proper decisions. Instead of offering competitive interest rates on saving accounts to attract stable deposits for credit applications, bank managers focus their attention on credit analysis to determine a borrower's ability to repay loans, along with collateral evaluation and documentation screening to protect the bank's financial profits and to make sure that deposit payments are duly made. Therefore, the role played by the banks of Taiwan is primarily to avoid the cost of type I error.

Recently, a case of bank failure happened in Taiwan in the year 2006 after the credit card and cash card crisis occurred. Therefore, we decide to collect data from the financial statements or annual reports of the banking industry in Taiwan for the purpose of empirical study. In order to identity the worst performers as potentially failed banks in advance, we need to study the real data for the year prior to failure happened. The financial data that fit for inputs, intermediate measures, and outputs are the source for measuring their worst efficiencies.

There were 29 banks (or their holding companies) listed on the security list of Taiwan Stock Exchange Corporation (TSEC) in the year 2005. All of them are included in this study, except for two banks. The first one is China Development Industrial Bank. This bank is an industrial bank and direct investment has been the core business of China Development Industrial Bank. The intermediate measure of deposits does not fit the production process of this bank. The second one is

Taiwan Cooperative Bank Co., Ltd. Under the Taiwan Cooperative Bank Charter, the Bank is charged with carrying out the missions of operating a banking business and providing financial adjustment for the farming and fishery industries. Therefore, Taiwan Cooperative Bank plays a role like the small central bank for cooperative groups, farmers' associations, fishermen's associations, and irrigation associations. This bank should be excluded from the data set of this study. All the remaining banks can be considered in the category of commercial banks.

The choice of inputs and outputs follows [2] and [6] as shown in Table 1. However, the information technology budget has not been shown in the financial statements or annual reports of the commercial banks in Taiwan. We exclude this index from our two-stage model. The indices used in our two-stage WPF-BCC model are inputs of assets and employees, intermediate measure of deposits, and outputs of profits and fraction of loans recovered. The data of 27 Taiwan banks are shown in Table 3. The monetary values are in million Taiwan dollars, where 1 US dollar is approximately equal to 30 Taiwan dollars. Of the 27 banks, bank 27 was taken over by the Financial Restructuring Fund of Taiwan in December 2006. This fund is controlled by the government of the Republic of China (Taiwan) to preserve financial stability, depositor interests, and social order in case of bank failure. If a bank is taken over by the fund, it is considered bankrupt. Our purpose is to effectively and accurately identify this failed bank through the use of two-stage WPF-BCC model.

Table 3. The financial data for 27 Taiwan commercial banks in the year 2005.

Bank	Assets X_1	Employees X_2	Deposits Z	Profits Y_1	Fraction of loans recovered Y_2 (%)
1	617,831	1,318	291,006	6,326	97.76
2	604,674	2,338	492,704	206	95.95
3	995,120	5,453	733,727	5,034	97.58
4	153,353	848	117,819	390	98.33
5	1,501,047	7,192	1,187,301	10,219	98.28
6	1,584,445	7,157	1,292,091	9,403	97.88
7	1,356,313	6,091	1,048,963	–36,516	98.33
8	1,228,078	3,555	794,714	11,392	99.50
9	1,074,061	4,190	794,042	3,853	98.27
10	328,979	3,641	271,831	–3,458	96.24
11	215,801	2,969	154,927	–561	94.04
12	305,656	2,339	228,053	1,407	98.17
13	308,868	2,815	257,447	52	97.51
14	522,510	2,171	398,499	2,117	98.99
15	563,425	3,139	440,483	3,830	99.21
16	255,685	3,471	221,826	111	96.63
17	851,262	8,215	670,564	–3,775	98.66
18	339,635	2,962	262,957	1,077	97.05
19	315,330	1,897	246,108	4	97.51
20	1,604,678	7,556	1,173,300	13,916	98.50
21	338,539	3,583	289,443	–259	97.61
22	1,045,415	5,063	880,248	–15,046	97.65
23	434,640	2,789	335,761	2,451	98.10
24	402,069	3,414	331,994	3,191	97.54
25	261,537	1,928	239,124	–1,003	97.99
26	154,406	1,545	135,153	–370	95.52
27	60,501	908	57,756	–728	86.37

3.2 Empirical Results

For the purpose of identifying the failed bank and comparing the discriminating power of the best-practice frontier and worst-practice frontier BCC models, we apply both BCC and WPF-BCC model to the data set in two stages. The data on Profits was translated as follows: Modified Profits = Profits + 36516, where –36516 is the smallest Profits value in

Table 3. The efficiency scores of BCC model in two stages and the worst-efficiency scores of WPF-BCC model in two stages are presented in Table 4.

Table 4. The results of two-stage BCC and WPF-BCC models.

Bank	Efficiency scores of BCC in stage 1	Efficiency scores of BCC in stage 2	Worst-efficiency scores of WPF-BCC in stage 1	Worst-efficiency scores of WPF-BCC in stage 2
1	1.000	1.000	1.000	4.332
2	1.000	0.217	1.362	2.107
3	0.871	0.344	1.058	1.682
4	1.000	1.000	1.306	10.562
5	0.964	0.571	1.053	1.088
6	1.000	0.462	1.013	1.000
7	0.944	0.112	1.083	1.000
8	1.000	1.000	1.000	1.626
9	0.959	0.330	1.107	1.590
10	0.917	0.395	1.116	3.842
11	0.779	0.621	1.000	5.415
12	0.816	0.646	1.219	5.480
13	0.919	0.442	1.239	4.644
14	0.932	0.903	1.340	3.146
15	0.906	1.000	1.265	2.866
16	0.948	0.493	1.051	4.988
17	0.927	0.356	1.000	1.823
18	0.856	0.514	1.167	4.393
19	0.903	0.462	1.362	4.857
20	0.891	1.000	1.000	1.101
21	0.954	0.395	1.165	4.159
22	1.000	0.130	1.197	1.267
23	0.874	0.530	1.246	3.739
24	0.933	0.597	1.205	3.670
25	1.000	0.486	1.498	5.173
26	0.947	0.767	1.325	7.329
27	**1.000**	**1.000**	**1.000**	**1.000**

What is really relevant is how to distinguish potentially failed bank(s) from the bad performers (worst efficient DMUs identified using WPF-BCC or inefficient DMUs identified using BCC) in two stages effectively and accurately.

In order to integrate the results of efficiencies from two stages, we introduce the business strategy matrix as a managerial decision tool. By using this tool, we can get more accurate results from a cross-identification process. Accordingly, we will find a few worst ones from plural bad performers when using BCC or WPF-BCC model in single stage. This is a fit for the real world situation that there is only a small portion of public companies filing for bankruptcy in an average year. For example, there were only three banks once on the security list of Taiwan Stock Exchange Corporation filed bankruptcy from 1997 to 2006. The real average bankruptcy ratio of the listed banks in Taiwan is about 1% in the recent decade.

The business strategy matrix of worst-efficiency scores in two stages using WPF-BCC are shown in Table 5. The business strategy matrix of efficiency scores in two stages using BCC are shown in Table 6. Obviously, two-stage WPF-BCC model can effectively identify bank 27 as a potentially failed bank. However, two-stage BCC model not only fails to rank the potentially failed bank to the last one, but even unexpectedly identifies bank 27 as efficient in both stages.

Table 5. The business strategy matrix of worst-efficiency scores in different stages using WPF-BCC.

Stage 1 \ Stage 2	Worst efficient	More efficient
More efficient	***Cows*** 1, 8, 11, 17, 20	***Stars*** 2, 3, 4, 5, 9, 10, 12, 13, 14, 15, 16, 18, 19, 21, 22, 23, 24, 25, 26
Worst efficient	***Dogs*** 27	***Sleepers*** 6, 7

Table 6. The business strategy matrix of efficiency scores in different stages using BCC.

Stage 1 \ Stage 2	Inefficient	Efficient
Efficient	***Cows*** 2, 6, 22, 25	***Stars*** 1, 4, 8, 27
Inefficient	***Dogs*** 3, 5, 7, 9, 10, 11, 12, 13, 14, 16, 17, 18, 19, 21, 23, 24, 26	***Sleepers*** 15, 20

4 Conclusion and Future Directions

The results of the empirical study show the validity of WPF-BCC model as a worst-efficiency measurement tool to identify potentially failed banks in a two-stage production process. In the real world, failed banks or firms could be loss-making for a period of time before they went into bankruptcy. There should be negative data such as negative profit in the outputs of performance indices. Therefore, the applied DEA models should be able to handle negative data in an empirical study, which is exactly the advantage of employing WPF-BCC model.

The applied approach in this study provides a new wide avenue for future researches. New approach of full ranking for the worst or best performances in the worst-case scenario would be a possible topic of future research. Cross-identification through the pessimistic point of view in combination with the optimistic point of view in order to improve the discriminating power can be another direction. Other extended WPF-DEA models, along with other approaches and applications, are also important to documenting its practicality.

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