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Operating efficiency and productivity measurement in Taiwan's banking industry

Abstract

While some past studies estimating technical efficiency include undesirable outputs, most treat undesirable outputs as inputs. Such treatment does not, however, reflect the true production process in the banking industry. This paper has two main contributions. The first is that it uses non-performing loans as the undesirable output in assuming weak disposability, which can reflect the true production process in the banking industry. The second is that it applies NL super efficiency and a productivity index from which we can obtain more information regarding the decision units. The results show that most banks exhibit decreasing returns to scale. Large-sized banks need to appropriately adjust their scale of operations, and small-sized banks can improve their pure technical efficiency by re-allocating their input and output resources.

Keywords: data envelopment analysis, NL super efficiency, Malmquist-Luenberger productivity index, and undesirable outputs.
JEL Classification: C61, G21.

Introduction

Financial institutions are a critical component of a modern economy that has undergone a process of transition towards internationalization and liberalization in recent years. Banks play the role of financial intermediaries not only in mediating the supply and demand for funds, but also in allocating funds and promoting economic development (Wachtel, 2003; Bertocco, 2008).

In 1990, the Ministry of Finance of Taiwan drew up the "Criteria for the Establishment of New Commercial Banks" and accepted applications for the setting up of new banks. Subsequently, many new banks were added and the banking industry in Taiwan became highly competitive. It is against such a competitive environment that the operational efficiency of banks has become an issue that deserves to be further analyzed. In terms of the measurement of efficiency value, the DEA method has been very popular, with the issue of the managerial efficiency of financial institutions having been widely explored. However, very few studies have focused on the issue of risk management efficiency. The main operational risk in the banking industry has been non-performing loans[1] (Yang and Lin, 2009), and thus many banks have tolerated high non-performing loans in order to increase their lending and enhance their performance.

Andersen and Petersen (1993) proposed the use of a super-DEA model in addition to the above-mentioned model. Their approach not only retains the rating of inefficient units as in the conventional DEA model, but also provides more information in regard to efficient units. Ray (2008) further modified the production possibility to construct a NL super efficiency model based on a directional distance function, which can consider the undesirable output. However, the former model does not consider the undesirable output and is not applicable to the production process in the banking industry, whereas the latter is applicable to the production process of banks as mentioned above. In this study, we further apply the NL super efficiency model to estimate NL super efficiency, from which we can obtain more information regarding the efficient units.

While the main source of the income of banks is from loans, too much lending may cause the non-performing loans to become so high that the banks' risks are increased. According to the study of Chen et al. (2007) for farmers' credit unions, both asset quality and risk factors need to be taken into consideration while in estimating efficiency, or else unions that expand excessively risky loans might be mistakenly treated as efficient.

The operational efficiency of banks in combination with their productivity index was used to analyze the competitiveness of each bank and the variation in efficiency for each bank. In order to measure productivity growth, Färe et al. (1989; 1994) developed a model named the Malmquist index (referred to as the M index hereafter) to estimate productivity index that require information only on input and output quantities. Their non-parametric M index measure depends

[1] "Non-performing loans" as defined by Banking Bureau, Financial Supervisory Commission, R.O.C, "as referred to in the Regulations shall refer to those loans for which the principal or interest has been in arrears for three months or more, and those loans for which the principal or interest has not yet been in arrears for more than three months, but with regard to which the bank has sought payment from primary/subordinate debtors or has disposed of collateral. If a restructured loan meets certain conditions, the negotiated interest rate is not lower than that of the original loan or the rates of new loans in the same risk category, and the negotiated terms have been performed for over six months, the loan may be exempted from being reported as a non-performing loan. However, if the negotiated instalment payments are in arrears for three months or more during the period of exemption as non-performing loans, the loan shall still be reported as such".

on creating a best frontier over whole samples observed and calculating the distances between individual observations and their frontier (Yörük and Zaim, 2005). However, when undesirable outputs are considered and must be incorporated into the M index, Chung et al. (1997) introduced a directional distance function to proposed a new M index, the Malmquist-Luenberger productivity index (the ML index hereafter), to measure productivity growth in the presence of the combined production of both desirable and undesirable outputs. Not only the reduction in undesirable outputs, but also the increase in desirable outputs is considered in the ML index. In addition, all the desirable properties of the M index are also included in the ML index. In spite of these benefits of ML index, limited approaches were made for empirical studies on measuring productivity growth using the ML index (Yörük and Zaim, 2005).

To summarize, the first purpose of this study is to test the hypothesis that, with or without undesirable outputs, different ratings will arise for the inefficient units of banks in Taiwan. If this assumption is correct, the second purpose of this study is to estimate the NL super efficiency of the banks in Taiwan while undesirable outputs are considered. Finally, this paper estimates the productivity index for 33 domestic banks in Taiwan with risk included as an undesirable output and measured by their respective non-performing loans.

1. Background to the banking industry in Taiwan.

Since the early 1980s, the Taiwan government has subsequently relieved many protectionist measures, and as a result Taiwan's financial industry has undergone several stages of regu latory reform. In order to establish a strong environment for the entry of new banks, Taiwan's legislature amended the Banking Act in July 1989. Shortly thereafter, the Ministry of Finance announced new standards for the establishment of commercial banks in April 1990 and accepted applications for new banks. On July 3, 1991, the Ministry of Finance approved the establishment of 15 new banks and one more in June 1992. Since 1993, 46 credit cooperatives have been either converted into commercial banks or else merged with or acquired by other financial institutions (Lin et al., 2007). As a result, the number of domestic banks has increased from 17 to 37, and the number of branches has increased from 1,046 to 3,279 over the 1991-2009 period. Furthermore, the financial authorities in Taiwan have also pushed the government-owned banks to become private banks by selling their shares through initial public offerings (IPO). Therefore, banking industry in Taiwan has faced highly competition since the early 1990s (Lai, 2001; Lin et al., 2007). The accumulation of non-performing loans and rising non-performing loan ratios[1] led to a sustained downgrade of the Asian economies during the 1990s culminating in the Asian financial crisis that occurred in 1997 (Kwack, 2000; Liu, 2009). In 2002, the quantity of non-performing loans of banks in Taiwan reached a new high of NT$312.0 billion and the non-performing loan ratio reached 3.52%. As a result of the government's adoption of various measures to deal with these problems, non-performing loans decreased by NT$285.1 billion and the non-performing loan ratio fell to 1.54% compared with the 2.25% of GDP recorded in 2008. However, although the statistics show that there was an improvement in the outstanding amount of non-performing loans and the non-performing loan ratio, the problems were still serious.

2. Literature review of undesirable outputs

The undesirable outputs that have been used to evaluate efficiency in the DEA model can be classified into four types. First of all, studies on the treatment of undesirable outputs as similar input items include Hailu and Veeman (2001) and Korhonen and Luptacik (2004). Chiu et al. (2008; 2011) further estimated the super efficiency in Taiwan's banking using a super-DEA model, and the undesirable output also was treated as an input. Seiford and Zhu (2002), however, argued that if the undesirable outputs were treated as inputs, such treatments did not reflect the true production process. Drake and Hall (2003) as well as Fukuyama and Weber (2008) also argued that, from a technical modelling viewpoint, the output possibility sets are unbounded if undesirable outputs are treated as inputs. Secondly, as the study of Lovell et al. (1995) showed, the carbon and nitrogen environmental disamenity exhibited a reciprocal relationship $(\frac{1}{undesirable\ output})$ with the vector of services and the undesirable output. Dyckhoff and Allen (2001) argued that the disadvantages of the treatment model were that it missed this characteristic and that the reciprocal of a zero value did not exist for the original data (Yang, 2006). Third, on the basis of the BCC classification invariance, each undesirable output was multiplied by "-1", and by adding an appropriate translation vector all negative undesirable outputs could then become positive as the studies of Ali and Seiford (1990), Seiford and Zhu (2002), and Li (2005) indicated. Yang (2006), however, argued that this approach was similar to that of Lovell et al. (1995) in which the undesirable outputs after being translated were identical to the desirable output, and thus tra-

[1] The non-performing loan ratio was calculated by dividing non-performing loans by total loans.

ditional methods could be applied to estimate efficiency. Fourth, the undesirable output was assumed to have weak disposability, indicating that reducing the undesirable output was costly, which meant that the decrease in undesirable outputs accompanied the decrease in desirable outputs or the increase in inputs (Färe et al., 1989; Chung et al., 1997; Yang, 2006).

Huang and Leung (2007), along similar lines to Färe and Grosskopf (2004), argued that the desirable outputs and undesirable outputs exhibited null-jointness. The properties of null-jointness mean that the undesirable outputs are also produced as the desirable outputs are produced. This means that if no desirable outputs are produced, then undesirable outputs are not possibly produced. Park and Weber (2006) as well as Fukuyama and Weber (2008) noted that non-performing loans (undesirable outputs) are treated as inputs in the treatment of non-performing loans, but that is not strictly true. The non-performing loans are produced by loans after the loans have been made. Therefore, it would not make sense to treat non-performing loans as an input or other translation mode in the banking industry.

To conclude, we found that it would be reasonable to assume that the undesirable output exhibits weak disposability in the banking industry. The operational strategy of banks should be to pursue a maximum of loans (operational management) and a minimum of non-performing loans (risk management). Thus, this study applies a directional output distance function as a measure for operational efficiency, and the efficiency of risk is taken into consideration simultaneously in order to maximize desirable outputs and minimize undesirable outputs.

3. Methodology

3.1. The directional distance function and efficiency measures. This paper intends to use Data Envelopment Analysis (DEA) as a tool for efficiency and productivity measurement. DEA, a mathematical programming approach that characterizes the relationships among multiple inputs and multiple outputs, was initiated by Charnes et al. (1978) who operated and extended the concept of production efficiency that had been put forth some twenty years earlier by Farrell (1957). Besides, as a nonparametric approach, DEA does not require an *a priori* functional specification of the unknown technology (Fukuyama, 1993; Favero and Papi, 1995; Yildirim, 2002). In addition, it provides a relative index of management for each individual bank without requiring price data (Fukuyama, 1993).

DEA measures the relative performance of decision-making units (DMUs) on the basis of the observed operating practice for a set of sample DMUs. Using production data for the sample DMUs, the approach sets up a piecewise linear production set. If both the input and output data of one DMU are on the frontier of the production set, the DMU is considered to be efficient. On the contrary, if its inputs and outputs fall within the frontier, the DMU is inefficient.

Up to now, there have been many alternative models developed by various researchers for their respective applications. In this paper, we regard the non-performing loans as an undesirable output in terms of a bank's operations. Unlike normal desirable outputs, reducing undesirable outputs is costly, which implies that it follows an assumption referred to as weak disposability. Färe et al. (1989) first considered these kinds of outputs and modified the standard Farrell-type efficiency measurement. Moreover, Chung et al. (1997) incorporated these kinds of outputs and developed a new index referred to as the ML index. Instead of the traditional Shephard output distance function, Chung et al. (1997) used a directional distance function which allows for the possibility of crediting firms for the decrease in undesirable outputs and inputs and for the increase in desirable outputs.

Assume that $x = (x_1, x_2 \ldots, x_M) \in R_+^N$ $y = (y_1, y_2, \ldots, y_M) \in R_+^M$ and that $u = (u_1, u_2, ..., u_J) \in R_+^J$ are the vectors of inputs, desirable outputs and undesirable outputs, respectively. The production technology can be described as:

$$T = \{(x, y, u) : x \text{ can produce } y \text{ and } u\}. \quad (1)$$

The directional distance function compares the sample observations with the efficient frontier based on the specified directional vector. For example, a directional output distance function based on the directional vector of $(g_y, -g_u)$ is defined as:

$$\vec{D}_o(x, y, u; g_y, -g_u) = \sup\{\beta : (x, y + \beta g_y, u - \beta g_u) \in T\}. \quad (2)$$

One can use $\vec{D}_o(x, y, u; g_y, -g_u)$ to measure the technical efficiency (TE) of observed outputs and inputs (x, y, u) for each observation based on the directional vector $(g_y, -g_u)$. That is,

$$TE = (1 + \vec{D}_o(x, y, u; g_y, -g_u))^{-1}. \quad (3)$$

In general, the directional vector $(g_y, -g_u)$ is set up by vector $(y, -u)$. Assume that there are K observations. For each individual observation k' in a specific time period t, the directional output distance function can be obtained by solving the following linear programing problem with a CCR model for constant returns-to-scale technology and a BCC model for variable returns-to-scale technology:

$$\vec{D}_o^t(x_{k'}^t, y_{k'}^t, u_{k'}^t; y_{k'}^t, \text{-}u_{k'}^t) = \max \beta$$
$$s.t. \sum_{k=1}^{K} z_k^t x_{kn}^t \le x_{k'n}^t, (n = 1,2,...,N)$$
$$\sum_{k=1}^{K} z_k^t y_{km}^t \ge (1+\beta) y_{k'm}^t, (m = 1,2,...,M)$$
$$\sum_{k=1}^{K} z_k^t u_{kj}^t = (1-\beta) u_{k'j}^t, (j = 1,2,...,J) \tag{4}$$
$$z_k^t \ge 0, (k = 1,2,...,K) \quad for\, CCR$$
$$z_k^t \ge 0, (k = 1,2,...,K); \sum_{k=1}^{K} z_k = 1 \ for\, BCC.$$

Model (4) considers undesirable outputs. If the output factors are ignored, by using the same model but dropping constraint $\sum_{k=1}^{K} z_k^t u_{kj}^t = (1-\beta) u_{k'j}^t$, one can calculate a distance function value which ignores undesirable outputs. Then, by using equation (3), a technical efficiency that does not consider undesirable outputs can also been obtained.

3.2. The NL super-efficiency measures. Owing to the efficiency scores for inefficient units and efficient units in the traditional DEA model being less than and equal to unity, respectively, Andersen and Petersen (1993) proposed a modified traditional DEA model, which can estimate efficiency scores larger than unity for efficient units. The approach involves the use of parametric methods to provide ranking and comparisons for efficient units. Ray (2008) modified the production possibility set to estimate NL super efficiency based on the directional distance function, which can consider the undesirable output model. In this study, we follow the computation of NL super efficiency proposed by Ray (2008) that contributes to obtaining more information for efficient units and is defined by

$$\vec{D}_o^t(x_{k'}^t, y_{k'}^t, u_{k'}^t; y_{k'}^t, \text{-}u_{k'}^t) = \max \beta$$
$$s.t. \sum_{\substack{k=1\\k\neq k'}}^{K} z_k^t x_{kn}^t \le x_{k'n}^t, (n = 1,2,...,N)$$
$$\sum_{\substack{k=1\\k\neq k'}}^{K} z_k^t y_{km}^t \ge (1+\beta) y_{k'm}^t, (m = 1,2,...,M)$$
$$\sum_{\substack{k=1\\k\neq k'}}^{K} z_k^t u_{kj}^t = (1-\beta) u_{k'j}^t, (j = 1,2,...,J) \tag{5}$$
$$z_k^t \ge 0, (k = 1,2,...,K; K \ne K') \ for\ CCR$$
$$z_k^t \ge 0, (k = 1,2,...,K; K \ne K); \sum_{\substack{k=1\\k\neq k'}}^{K} z_k = 1 \ for\ BCC.$$

If firm K is NL super efficient, $\beta < 0$ implies that the firm still maintains efficient even though the desirable outputs are scaled down and undesirable outputs are scaled up while the inputs remain unchanged. The rank is larger while β is relatively lower.

3.3. The ML measures. In this paper, the authors use the output-oriented ML productivity index developed by Chung et al. (1997) to estimate the productivity of banks, which is defined as

$$ML_t^{t+1} = \left[\frac{(1+\vec{D}_o^t(x^t, y^t, u^t; y^t, \text{-}u^t))(1+\vec{D}_o^{t+1}(x^t, y^t, u^t; y^t, \text{-}u^t))}{(1+\vec{D}_o^t(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1}))(1+\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1}))} \right]^{1/2}. \tag{6}$$

The index can be further decomposed into two components – efficiency change (*EFFCH*) and technical change (*TECH*) (Färe et al., 1994; Chung et al., 1997). Efficiency change (*EFFCH*) represents the ratio between the relative efficiency of a DMU in period $t + 1$ against that in period t, which can be represented by

$$EFFCH_t^{t+1} = \left[\frac{(1+\vec{D}_o^t(x^t, y^t, u^t; y^t, \text{-}u^t))}{(1+\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1}))} \right]. \tag{7}$$

Technical change (*TECH*) captures the shift in technology between the two periods t and $t + 1$, that is,

$$TECH_t^{t+1} = \left[\frac{(1+\vec{D}_o^{t+1}(x^t, y^t, u^t; y^t, \text{-}u^t))(1+\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1}))}{(1+\vec{D}_o^t(x^t, y^t, u^t; y^t, \text{-}u^t))(1+\vec{D}_o^t(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1}))} \right]^{1/2}. \tag{8}$$

The authors need to calculate four directional distance functions before obtaining this productivity index and its components. They are $spread_{it} = \beta_{0i} + \beta_{1i}\, growth_{it} + u_{it}$, $\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1})$, $\vec{D}_o^t(x^t, y^t, u^t; y^t, \text{-}u^t)$ and $\vec{D}_o(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1})$. Each of them may also be calculated as solutions to linear programing problems. As the general form:

$$\vec{D}_o^{t+s}(x_{k'}^{t+v}, y_{k'}^{t+v}, u_{k'}^{t+v}; y_{k'}^{t+v}, \text{-}u_{k'}^{t+v}) = \max \beta$$

$$s.t. \sum_{k=1}^{K} z_k^{t+s} x_{kn}^{t+s} \le x_{k'n}^{t+v}, (n = 1, 2, ..., N; s, v = 0, 1)$$

$$\sum_{k=1}^{K} z_k^{t+s} y_{km}^{t+s} \ge (1+\beta) y_{k'm}^{t+v}, (m = 1, 2, ..., M) \quad (9)$$

$$\sum_{k=1}^{K} z_k^{t+s} u_{kj}^{t+s} = (1-\beta) u_{k'j}^{t+v}, (j = 1, 2, ..., J)$$

$$z_k^{t+s} \ge 0, (k = 1, 2, ..., K).$$

The distance function $\vec{D}_o^{t+1}(x^t, y^t, u^t; y^t, \text{-}u^t)$ is calculated by replacing (s,v) with (1, 0), and similarly, $\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1})$, $\vec{D}_o^{t}(x^t, y^t, u^t; y^t, \text{-}u^t)$ and $\vec{D}_o^{t}(x^{t+1}, y^{t+1}, u^{t+1}; y^{t+1}, \text{-}u^{t+1})$ are calculated by replacing (s,v) with (1, 1), (0, 0) and (0,1), respectively.

4. Empirical results

4.1. Data and variables. In choosing the variables for the input items and output items for the banking industry, there are several approaches that can be adopted, namely, the intermediation approach, production approach, asset approach, user cost approach and value-added approach. This study applies the intermediation approach, whose viewpoint originates from the banks playing the role of financial intermediaries. The relevant data on the input and output items were obtained from the database of the Taiwan Economic Journal for the period from 1999 to 2008. The data were deflated by the consumer price index (CPI) for each year with 2006 as the base year. In selecting the variables, we referred to the intermediation approaches by Yue (1992) and Miller and Noulas (1996). The three desirable outputs items for each bank were Y_1, Y_2, and Y_3 with Y_1 denoting the interest income; Y_2 denoting the non-interest income; and Y_3 denoting the loans. The three input items were X_1, X_2, and, X_3, with X_1 denoting the interest expenses; X_2 denoting the non-interest expenses; and X_3 denoting the deposits. The one undesirable output item was u denoting the non-performing loans[1]. The summary statistics and characterizations are shown in Table 1.

Table 1. Summary statistics of input-output data for domestic banks in Taiwan in 1999-2008 (NT$ millions)

		Mean	Std. dev.
Output items	Total loans (Y_1)	398.680.338	406.532.931
	Interest income (Y_2)	23.144.622	22.208.393
	Non-interest income (Y_3)	12.221.045	31.126.952
Input items	Deposits (X_1)	510,293.074	533,225.917
	Interest expenses (X_2)	13,637.606	16,011.574
	Non-interest expenses (X_3)	20,477.112	33,569.009
Undesirable item	Non-performing loans (u)	12,415.671	16,001.318

[1] The study replaces three missing samples with related ones in a close period among 330 non-performing loan samples.

4.2. Results of operational efficiency. In the DEA model, we have focused on two hypotheses. One is to assume that the operations of banks entail no risk, that is to say, banks produce desirable outputs without accompanying undesirable outputs, and the other one is to assume that the operations of banks come along with risks, that is to say, banks produce desirable outputs accompanied by an undesirable output. This paper mostly uses the over technical efficiency (CRS), pure technical efficiency (VRS), scale efficiency (SE), NL super efficiency (NL), and ML index (ML) to explain the results in a more straightforward manner.

Because the efficiencies can not be compared directly when considering risk and when there is no risk since they are applied to different frontiers, the relative efficiency in this paper has been ranked in order to understand whether the real relative efficiency as well as the ranking for banks in terms of their efficiency appears to exhibit discrepancies. Spearman's rank correlation statistic when considering risk and when considering no risk was calculated and found to be 0.659 for CRS, 0.674 for VRS and 0.619 for SE, respectively. The results exhibited significant differences at the 1% significance level as shown in Table 2. The authors next discuss the model that takes the existence of risk into consideration, since the failure to consider risk not only goes against reality but also gives rise to different results from when risk is considered.

Table 2. Spearman's rank correlation test between no risk and risk for CRS and VRS

Rank	Method	Statistics
CCR for no risk vs. risk	Spearman rank correlation coefficient	0.659***
BCC for no risk vs. risk		0.674***
SE for no risk vs. risk		0.619***

Note: *** Denotes the 1% significance level of the statistical values.

Over the period from 1999-2008, when banks' overall technical efficiency were estimated, the potential improvements in inputs and outputs were 5.291% when risk was considered and 2.917% when risk was not considered. These increases were only 2.690% for considering risk and 1.478% for not considering risk if scale efficiencies were not considered. In terms of the returns to scale, the results indicated that the Taiwanese banks were more likely to exhibit decreasing returns to scale than increasing returns to scale. Thus, the inputs were excessive for banks characterized by non-constant returns to scale, so that such banks should appropriately reduce the scale of their inputs.

4.3. The returns to scale vs. efficiency. In Table 3, we further discuss the CRS, VRS, and SE for the returns to scale of banks. The results further show that the optimal operation of 120 increased to 194 when operational risk was considered. These results imply that these banks must pay attention to risk management in addition to engaging in normal business activities. When risk was considered, the SE for the banks with increasing returns to scale (IRS) was found to be significantly higher than that for banks with decreasing returns to scale (DRS), but the VRS of the IRS banks were significantly smaller than those for the DRS banks. These results imply that the DRS banks were seriously diverging from their optimal scale, but that the pure technical efficiency (VRS) of the DRS banks was higher than that of the IRS banks. Thus, for the DRS banks, adjusting their scale of operations wasmore significant than improving the pure technical efficiency of their inputs and outputs

Table 3. The difference test for the returns to scale of banks in considering no risk and risk

		N	Mean	Std. dev.	*F*-test	
No risk	*CRS*	*DRS*	33	0.906	0.061	113.249***
		CRS	120	1.000	0.000	
		IRS	177	0.919	0.061	
	VRS	*DRS*	33	0.925	0.058	45.082***
		CRS	120	1.000	0.000	
		IRS	177	0.964	0.055	
	SE	*DRS*	33	0.981	0.042	54.098***
		CRS	120	1.000	0.000	
		IRS	177	0.954	0.048	
Risk	*CRS*	*IRS*	21	0.921	0.061	169.677***
		CRS	194	1.000	0.000	
		DRS	115	0.931	0.052	
	VRS	*IRS*	21	0.928	0.061	69.277***
		CRS	194	1.000	0.000	
		DRS	115	0.971	0.046	
	SE	*IRS*	21	0.992	0.012	119.564***
		CRS	194	1.000	0.000	
		DRS	115	0.959	0.038	

Note: *** Denotes the 1% significance level of the *F*-values.

4.4. The banks' operating scale vs. efficiency. In terms of the operating scales of banks, the banks were classified into those with total assets of less than NT$200,000 million, of between NT$200,000 million and NT$500,000 million, and in excess of NT$500,000 million. Banks falling within these categories were referred to as small-sized banks, medium-sized banks and large-sized banks, respectively. The results from examining the CRS, VRS and SE for these different scales of operations are presented in Table 4. The results showed that the CRS and SE of small-sized banks were significantly higher than those of other banks, and that the VRS of small-sized banks and medium-sized banks was significantly smaller than that of large-sized banks at the 5% significance level. Thus, the results revealed that the advantages of the small-sized banks were scale efficiency and large-sized banks were pure technical efficiency, respectively. The results imply that the scale of the large-sized banks was seriously diverging from their optimal scale, so that they needed to adjust their operating scales appropriately. In turn, the small-sized banks could improve their pure technical efficiency through the re-allocation of their input and output resources.

Table 4. The difference test of CRS, VRS, and SE for three scales in considering no risk and risk

			N	Mean	Std. dev.	*F*-test
No risk	*CRS*	Less than NT$200,000 mn	96	0.953	0.064	2.083
		Between NT$200,000 mn and NT$500,000 mn	115	0.938	0.065	
		Greater than NT$500,000 mn	119	0.952	0.059	

Table 4 (cont.). The difference test of CRS, VRS, and SE for three scales in considering no risk and risk

			N	Mean	Std. dev.	*F*-test
	VRS	Less than NT$200,000 mn	96	0.964	0.056	24.522***
		Between NT$200,000 mn and NT$500,000 mn	115	0.956	0.060	
		Greater than NT$500,000 mn	119	0.997	0.012	
	SE	Less than NT$200,000 mn	96	0.989	0.029	21.218***
		Between NT$200,000 mn and NT$500,000 mn	115	0.981	0.030	
		Greater than NT$500,000 mn	119	0.954	0.055	
Risk	*CRS*	Less than NT$200,000 mn	96	0.978	0.046	3.964**
		Between NT$200,000 mn and NT$500,000 mn	115	0.961	0.057	
		Greater than NT$500,000 mn	119	0.975	0.041	
	VRS	Less than NT$200,000 mn	96	0.982	0.040	14.797***
		Between NT$200,000 mn and NT$500,000 mn	115	0.974	0.048	
		Greater than NT$500,000 mn	119	0.999	0.008	
	SE	Less than NT$200,000 mn	96	0.995	0.015	10.835***
		Between NT$200,000 mn and NT$500,000 mn	115	0.986	0.026	
		Greater than NT$500,000 mn	119	0.977	0.038	

Notes: ** Denotes the 5% significance level of the *F*-values. *** Denotes the 1% significance level of the *F*-values.

4.5. The NL super efficiency vs. productivity index. Based on the above-mentioned model, there were many efficient units and since the efficiency was equal to unity, we tried to use NL super efficiency (NL) to acquire more information according to Ray (2008) and introduced the ML index as established by Chung (1997). In terms of the productivity index, we verified two parts. The first part involved estimating the productivity index of the banks, which could be divided into efficiency change (*MLEFFCH*) and technical change (*MLTECH*). The second part was to estimate *MLEFFCH*, which could further be divided into pure technical efficiency (*MLPTE*) and scale efficiency (*MLSE*).

The above analysis can be used as a good reference for the formulation of NL super efficiency and productivity. These banks can be classified into four categories. In the first category, the banks have excellent super efficiencies and progress in productivity. In considering risks, these banks could increase their risks as well as reduce all of their outputs by an average of 41.3% in maintaining the input constant, and these banks could still maintain their efficiency relative to that of the banks of other groups. The progress in terms of productivity is derived from technical improvement but there is also a regression in efficiency. The reason for this regression in efficiency is not due to scale inefficiency but rather to technical inefficiency. The results show that most categories of three scale banks are located in Quadrant 1. In the second category, although the average super efficiency of these banks is greater than unity, the productivity exhibits a serious regression in efficiency. There are many large-sized banks located in Quadrant 2. These banks could increase their risks as well as reduce all of their outputs by 31.4% on average, and these banks could still maintain their efficiency relative to the banks in other groups. However, the average productivity of these banks is the lowest. The efficiency change and technical change of these banks has deteriorated, and the pure technical efficiency and scale efficiency have also deteriorated. In the third category, the super inefficiency and productivity are seen to have deteriorated for these banks. The potential improvement is 7.4% for these banks, and the index for all the banks has deteriorated in regard to the productivity index apart from pure technical efficiency, which has slightly improved. In the fourth category, the NL is inefficient and the potential improvement is 9.2% for these banks, but the productivity index of these banks exhibits progress. There are many small-sized banks and medium-sized banks located in Quadrant 4. Although the average NL was the lowest, the productivity indexes of these banks were more than unity. Thus, these banks possessed the greatest ability in terms of being able to improve.

Table 5. The difference test for four quadrants of banks based on the NL and productivity index

		N	Mean	Std. dev.	*F*-test
NL	Quadrant 1	102	1.413	1.592	5.434***
	Quadrant 2	68	1.314	0.596	
	Quadrant 3	55	0.926	0.075	
	Quadrant 4	72	0.908	0.101	

Table 5 (cont.). The difference test for four quadrants of banks based on the NL and productivity index

		N	Mean	Std. dev.	*F*-test
ML	Quadrant 1	102	1.095	0.129	74.241***
	Quadrant 2	68	0.889	0.097	
	Quadrant 3	55	0.918	0.087	
	Quadrant 4	72	1.111	0.125	
MLEFFCH	Quadrant 1	102	0.995	0.034	18.210***
	Quadrant 2	68	0.971	0.069	
	Quadrant 3	55	0.994	0.071	
	Quadrant 4	72	1.043	0.068	
MLTECH	Quadrant 1	102	1.102	0.141	40.790***
	Quadrant 2	68	0.918	0.105	
	Quadrant 3	55	0.927	0.103	
	Quadrant 4	72	1.069	0.149	
MLPTE	Quadrant 1	102	0.995	0.017	15.520***
	Quadrant 2	68	0.978	0.052	
	Quadrant 3	55	1.003	0.053	
	Quadrant 4	72	1.030	0.060	
MLSE	Quadrant 1	102	1.000	0.026	6.064***
	Quadrant 2	68	0.993	0.042	
	Quadrant 3	55	0.990	0.035	
	Quadrant 4	72	1.013	0.034	

Note: *** Denotes the 1% significance level of the *F*-values.

Conclusions

Although some studies in the past have estimated technical efficiency while taking undesirable outputs into consideration, few have attempted to apply the directional distance function. This paper has two main contributions. The first one is that we have used the non-performing loans as the undesirable output and assumed weak disposability. Such a model reflects the true production process better than other models in the banking industry. The authors have therefore, applied the directional distance function to estimate efficiency and the productivity index both by taking and not taking undesirable outputs into consideration and ranking them. If the rank is not significantly different when undesirable outputs are either taken or not taken into consideration when estimating efficiency, the models can be simplified to estimate efficiency and the productivity index directly as consideration is only given to desirable outputs. The results are significantly different when undesirable outputs are not considered or are considered in terms of efficiency and the productivity index. Thus, in this paper, the estimation of efficiency and the productivity index for Taiwanese banks can not be simplified, meaning that both the desirable outputs and undesirable outputs must be simultaneously considered. For the second contribution, we apply NL super efficiency as well as a productivity index that can enable us to obtain more information for efficient units, while few have attempted to apply the NL super efficiency.

Being a small island with many commercial banks, financial holding banks and farmers' associations, maintaining a high degree of competitiveness has been an important issue in Taiwan. This study has contributed to other aspects in evaluating the inefficiencies of banks and in helping to look for technical efficiency improvement strategies based on the benchmarking of those potentially efficient banks.

Due to the limitations of the data, this study has only considered domestic banks in Taiwan, and the other operational types of banks have been excluded. Finally, this study draws comparisons in terms of the comparable efficiency of different scales of bank. Future studies on banks could follow this paper as an alternative approach to facilitating the estimation of efficiency.

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