REDUCTION OF NON-PERFORMING LOANS IN THE BANKING INDUSTRY: AN APPLICATION OF DATA ENVELOPMENT ANALYSIS

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Abstract. The increase in non-performing loans around the world has had quite a negative impact on many nations' banking systems. To address these problems, many creative regulatory solutions and well-designed risk techniques have been utilized in the hope of reducing non-performing loans to an acceptable level. The purpose of this study is to apply a newly developed data envelopment analysis model to suggest the most efficient plan (called Plan 4) to reduce non-performing loans that can maximize the efficiency of the entire banking industry's control over the bad debts. For comparison purpose, three other reduction plans are also represented. The four plans are presented using data from Taiwan's banking industry. The empirical results show that among the plans presented, Plan 4 shows the most effective allocation of the industry-wide reduction target. The plan focuses on a finite number of banks, helping identify the key units to improve industry-wide efficiency. The findings implicitly suggest that the regulator should devise more incentive measures to encourage target banks to perform the non-performing loan reduction task. Our results also suggest that for the regulator, forcing banks to cut their non-performing loans by the same ratio will not help improve the relative efficiency of the industry.

Keywords: banking industry, non-performing loan, risk management; data envelopment analysis, undesirable output, Taiwan.

JEL Classification: C44, C61, D24, G21.

Introduction

The global financial crisis has, since its onset in 2008, taken a toll on the world economy. Accompanying the crisis has been a severe contraction in economic activity. Financial institutions facing the crisis generally have exhibited unsafe and unsound practices. As a result, the quality of loan portfolios has deteriorated significantly, causing an increase in non-performing loans (NPLs) and sizeable profit reduction in banking systems. Because of their rising volume and their impact on the economy as a whole, on the banking system and on its credit supply, NPLs have been an increasingly hot topic in the international scene (Scardovi 2016).

To control NPLs, the implementation of a well-designed risk management framework has been considered a must for a best-practice bank. To decide whether to approve a loan application, banks should evaluate the riskiness of the loan, decide an appropriate risk premium on the loan, devise measures to prevent as well as deal with possible loss events, and assess their ability to absorb losses when NPLs occur. Putting such a framework into practice would be expected to increase operational efficiency. If the risk management framework does not work, a plan for the reduction of NPLs is necessary.

Two interesting issues arise during the process. The first one is the role of NPLs in efficiency analysis and their impact on operational efficiency, which have drawn much attention from academic researchers. To investigate the problems, earlier studies generally used a two-stage approach. First, they estimated bank efficiency, and then used regression techniques, in which NPLs are an explanatory variable, to analyze the impact of the NPLs on efficiency. A general conclusion is that NPLs had a negative effect on efficiency (see e.g. Mester 1996; Berger, DeYoung 1997). The two-stage approach, however, does not include NPLs in efficiency estimation models. Assaf *et al.* (2013) argued that, in this way, the resulting efficiency scores are biased. The efficiency measure may overestimate a bank's performance if it produces a high percentage of NPLs, and underestimate those producing less. Fujii *et al.* (2014) also argued that neglecting NPLs will fail to credit a bank for its effort to deal with the undesirable outputs. A banking production process must be clearly defined based on both desirable and undesirable outputs.

The second issue is how to reduce NPLs. Research on this topic has generally studied the effect of creative regulatory solutions or management programs on the control over NPLs. For example, Erdinç and Gurov (2016) examine whether the implementation of advanced risk management techniques in compliance with the internal ratings-based approaches in the Basel Capital Accord reduced NPLs. Saha *et al.* (2016) propose a knowledge-driven automated compliance auditing scheme for the processing of loans to investigate whether loan applications are highly risky. Stijepović (2014) recommends a project called the Podgorica Approach for quantitative assessment of the recovery of NPLs which could return to performing status through a restructuring process. Other studies seek solutions to reduce NPLs by finding their determinants; see e.g. Vithessonthi (2016), Louzis *et al.* (2012), and Ghosh (2015).

The present article follows the strand of the first issue. The novelty is that we incorporate the second issue into bank efficiency analysis. When evaluating bank efficiency, "data envelopment analysis" (DEA) is considered a suitable and commonly used approach (Fethi, Pasiouras 2010; Luo 2003). This is especially true when NPLs are considered, because DEA can easily accommodate both multiple inputs and multiple outputs. In DEA literature, NPLs are termed undesirable outputs, being distinguished from standard outputs. From the viewpoint of efficiency evaluations, given a specific amount of inputs, the more standard outputs are produced, the more efficient a production unit is. Yet producing fewer undesirable outputs is better. Most existing bank efficiency works that considered NPLs just focused on the issue of efficiency and productivity analysis; see e.g. Zhu *et al.* (2015). To our knowledge, no studies have been conducted in the literature so far to address the problem of NPL reduction by using DEA.

However, a few studies that use parametric approaches to explore the effect of NPLs on bank efficiency can also deal with the problem of NPL reduction in a different way. Pastor and Serrano (2005) measure a ratio between the minimum NPLs and observed NPLs, called risk management efficiency, with which one can evaluate by how much a bank should decrease NPLs to be efficient. Maggi and Guida (2011) estimate the cost function for Italian banks, and calculate the NPL impact on the operating cost. They represent the link between loans and NPLs by stressing the role of the geographical position of the bank, and gauge such geographical differences as extremely relevant to the possibility of controlling costs by reducing the level of loans and NPLs according to the performance of the different areas. Instead of using parametric approaches, the present paper applies non-parametric DEA approaches, which do not require any definitions to be made about a specific form of an underlying production function. Besides, the proposed approach can measure both the industry-level and bank-level performance of controlling NPLs, and disaggregate the industry-wide reduction target into the aim of each bank, which earlier studies using parametric approaches did not consider.

As such, the purpose of this study is to contribute to the literature by suggesting a newly developed DEA model for deriving a NPL reduction plan that improves industry efficiency most. We present and compare four NPL reduction plans, including (1) reduction according to a given rate of decrease, (2) reduction according to the efficiency with which a bank controls NPLs, (3) reduction according to a mixed strategy combining the first two, and (4) reduction suggested from the proposed DEA model to maximize the industry-wide efficiency of controlling NPLs. We use a dataset collected from Taiwan's banking industry to conduct an empirical study. The main finding is that Plan 4 can help identify a finite number of key banks to improve system efficiency most.

The remainder of this paper unfolds as follows. The next section discusses the existing DEA-based approaches for the reduction of undesirable outputs. Section 2 introduces the methodological issues and explains the details of the suggested reduction plans. Section 3 presents the data. In Sections 4 and 5, the empirical findings are presented and discussed.

1. DEA models for controlling undesirable outputs: a brief review

Our proposed models are based on a DEA-like approach. Before introducing the proposed models, it is necessary to explain where the suggested approach is grounded in the literature. As mentioned earlier, although there have been a large number of DEA publications involving empirical research on the banking industry, most of them have been published in the field of efficiency and productivity analysis. None have conducted studies on the reduction of NPLs. However, a few DEA studies have addressed the issue of allocating a reduction target of pollutants or greenhouse gas emissions among decision-making units (DMUs), which are also termed undesirable outputs.

Wu *et al.* (2013) introduce a bargaining game into a centralized DEA model so that DMUs compete with each other for the least reduction of emission permits. In doing so, the central authority can improve the overall efficiency by reallocating the remain-

ing emission permits. The proposed approach is applied to a dataset of agricultural greenhouse gas emissions from 15 European Union members. Sun *et al.* (2014) discuss two mechanisms for the reduction of emission permits among a group of manufacturing companies. The first one supposes that one of the member firms dominates the allocation on behalf of the group, and the second one assumes that a central authority is responsible for coordinating the allocation among all group members. The result shows that the second mechanism, which can not only maximize the whole efficiency of the group but also improve efficiencies of individual firms, is a better choice than the first one.

Feng *et al.* (2015), however, argue that a centralized allocation plan suffers from an implementation difficulty in persuading DMUs to reach agreement. They propose a two-step method to mitigate this side effect. In the first step, they provide improved DEA-based centralized allocation models, and in the second step, two compensation schemes are developed for centralized allocation for carbon emission abatement across countries in the Organization for Economic Co-operation and Development. Wu *et al.* (2016b) incorporate DEA and its closest target technique into a carbon emission abatement allocation problem. First, they propose a two-stage optimal total abatement target identification approach, which is used to obtain the optimal total abatement level for the DMUs. Then, another two-stage approach is developed for allocating the optimal total abatement among the DMUs. Wu *et al.* (2016a) suggest a context-dependent DEA technique, which maximizes output revenue after the total reduced carbon dioxide emissions and energy intensity, to allocate national carbon dioxide emissions and energy intensity reduction targets over Chinese provincial industrial sectors.

Another series of studies employ zero sum gains DEA models to "reallocate" emission permits or pollutant emissions. Note that a zero-sum game or a reallocation plan means that the total undesirable outputs remain unchanged, rather than reduced, after allocation. However, we believe that after appropriate revision the models can also be applied to allocate reduction targets over DMUs. Gomes and Lins (2008) are the first applying the models. They evaluate a carbon dioxide emission reallocation scheme between non-Annex I and Annex I parties, which can be considered part of the Kyoto Protocol statement. For more related studies, see Pang *et al.* (2015) and Chiu *et al.* (2015).

The above brief review shows that, as we have noted earlier, no DEA studies have addressed the problem of NPL reduction. Previous studies just focused on one type of undesirable outputs–pollutants. And the proposed DEA-like approaches could be classified into two categories: centralized DEA and zero sum gains DEA. The suggested approaches either emphasize that a central agency vigorously intervenes in the allocation of reduction or introduce negotiation mechanisms for the allocation of reduction. Both the proposed models are mainly applied to deal with emission abatements between countries. Neither of them has developed schemes from the viewpoint of maximizing industry efficiency. In the banking industry, it is important to control NPLs from the viewpoint of the industry. As argued by Scardovi (2016), banks may not possess the skills necessary to develop a strategy that takes into account an industry-wide perspective. In the present article, we have considered this perspective by introducing new approaches.

2. Methodological issues and plans for the reduction of undesirable outputs

2.1. Measuring the efficiency of controlling undesirable outputs

The proposed approaches aim at developing the best plan for the reduction of NPLs. Before introducing the suggested models, it is necessary to clarify how the best plan is defined. Since the central topic is to deal with NPLs, naturally the measurement of how efficiently NPLs are controlled would be an ideal index, and a plan that can maximize the index would be the best.

Assume that the banking industry evaluated is composed of $n = 1,\ldots,N$ banks or DMUs. Each consumes inputs $x_1,\ldots,x_I$ to produce outputs $y_1,\ldots,y_J$, and in the process NPLs occur, which are considered undesirable outputs. To generalize the proposed models, assume that there are $b_1,\ldots,b_K$ undesirable outputs. Let x_{in}, y_{jn} and b_{kn} respectively denote the ith input, the jth output and the kth undesirable output of DMU n.

We use the concept of "sub-vector efficiency" (Frija *et al.* 2009; Pang *et al.* 2015), which is introduced to account for undesirable output dimensions only, to measure the efficiency of controlling undesirable outputs, i.e. the efficiency of controlling NPLs (E-NPL) in our case. The efficiency measure is basically similar to traditional radial measures. The general specification for evaluating E-NPL of DMU $o \in \{1,\ldots, N\}$ is as follows:

$$Min \; \theta \tag{1.1}$$

$$s.t. \; \sum_{n=1}^{N} \lambda_n x_{in} \leq x_{io}, \; i = 1,\ldots, I; \tag{1.2}$$

$$\sum_{n=1}^{N} \lambda_n y_{jn} \geq y_{jo}, j = 1,\ldots,J; \tag{1.3}$$

$$\sum_{n=1}^{N} \lambda_n b_{kn} \leq \theta b_{ko}, \; k = 1,\ldots, K; \tag{1.4}$$

$$\sum_{n=1}^{N} \lambda_n = 1; \tag{1.5}$$

$$\lambda_n \geq 0, n = 1,\ldots,N; \tag{1.6}$$

$$\theta \; \text{is unconstrained in sign}, \tag{1.7}$$

where θ is a shrinkage factor with a boundary between one and zero for the undesirable outputs, namely the measure of E-NPL in our case. $\theta < 1$ shows a technically inefficient DMU because there exist undesirable output shrinkages. $\theta = 1$ shows a technically efficient DMU because of no undesirable output shrinkages. A more illuminating exposition of the measure can be found when Model (1) is rewritten as a dual form, which we will explain later. λ are non-negative weights that define the target operation unit as a linear combination of the sample observations. (1.5) is a convexity constraint, which allows the production technology to display variable returns to scale. Without this constraint, the production technology is assumed to exhibit constant returns to scale, which indicates that DMUs are operating at their optimal scale. Because there is no evidence

to show that the banks under evaluation in this study are at their optimal scale, the underlying technologies are assumed to be variable returns to scale.

Another way that Model (1) is different from traditional models is that it includes undesirable outputs. In DEA literature, however, there has been so far no general agreement on modeling undesirable outputs in a model; for a discussion on this matter see, e.g., Liu *et al.* (2010). Before a general conclusion is reached, we consider all existing approaches to be valid. When measuring E-NPL, if outputs are given, a DMU producing fewer undesirable outputs is considered more efficient, and so is using fewer inputs. Therefore, many studies (e.g. Zhang 2008) treat undesirable outputs as inputs. Both inputs and undesirable outputs are something that is given, needed, or lost in order to get a particular desirable output. For a bank, issuing riskier loans and using more inputs should produce more revenue and gains, yet riskier loans are frequently accompanied by NPLs. Thus, in a service process of commercial banks, NPLs are treated as inputs (Pasiouras 2008).

Model (1) is used to measure E-NPL at the DMU level. What about the E-NPL at the "industry" level? To address this question, we modify the approach suggested by Ray and Hu (1997) to develop the desired model. Since the banking industry is made up of individual banks, let the industry's inputs, outputs and undesirable outputs be denoted by *X, Y* and *B*. Then the observed data are

$$X_i = \sum_{n=1}^{N} x_{in}, \; i = 1,\dots, I; \tag{2}$$

$$Y_j = \sum_{n=1}^{N} y_{jn}, \; j = 1,\dots, J; \tag{3}$$

$$B_k = \sum_{n=1}^{N} b_{kn}, \; k = 1,\dots, K. \tag{4}$$

A DEA model typically consists of two parts, the production possibility set and the evaluated point. As shown in Model (1), the observed data (x_{io}, y_{jo}, b_{ko}) are placed on the right-hand sides of the constraints (1.2)–(1.4), and the production frontier is formulated as the left-hand sides of the same constraints. The scale of an industry on average is N times as large as an individual bank, so the industry's production possibility set would be expanded outward N times more than those of (1.2)–(1.4). Let $\eta_n = N\lambda_n$, and replace (x_{io}, y_{jo}, b_{ko}) with (X_i, Y_j, B_k). The model measuring industry-level E-NPL is as follows:

$$Min \;\; \theta \tag{5.1}$$

$$s.t. \;\; \sum_{n=1}^{N} \eta_n x_{in} \leq X_i, \; i = 1,\dots, I; \tag{5.2}$$

$$\sum_{n=1}^{N} \eta_n y_{jn} \geq Y_j, j = 1,\dots, J; \tag{5.3}$$

$$\sum_{n=1}^{N} \eta_n b_{kn} \leq \theta B_k, \; k = 1,\dots, K; \tag{5.4}$$

$$\sum_{n=1}^{N}\eta_n = N; \tag{5.5}$$

$$\eta_n \geq 0, n = 1, \ldots, N, \tag{5.6}$$

$$\theta \text{ is unconstrained in sign.} \tag{5.7}$$

We now turn to the issue of the reduction of undesirable outputs. Suppose that the industry wants to reduce undesirable outputs by $\alpha_k \beta_k$, where α_k is a reduction rate of the kth undesirable output, $0 < \alpha_k < 1$. Then the next question is how much each DMU should reduce undesirable outputs. We suggest using the following formula to derive possible plans.

$$d_{kn} = \beta_k b_{kn} + \left(\frac{1-\theta_n^*}{\sum_{o=1}^{N}(1-\theta_o^*)}\right)(\alpha_k - \beta_k)\, B_k\, , \ n = 1, \ldots, N\,; \ k = 1, \ldots, K, \tag{6}$$

where d_{kn} denotes the reduction of the kth undesirable output of DMU n, and θ^* is DMUs' E-NPL before reduction. Specifically, formula (6) divides α_k into two parts, β_k and $\alpha_k - \beta_k$, where β_k is a plan parameter, $\beta_k \leq \alpha_k$. Defining β_k with different numerical values, various reduction plans are suggested. We further define a DMU's responsibility of reduction as consisting of two parts accordingly. The first part, $\beta_k b_{kn}$, delimits a given responsibility for each DMU according to its own NPLs. The more NPLs a DMU produces, the more reduction it should undertake. The second part, $\left(1-\theta_n^*\right)\left(\alpha_k - \beta_k\right)B_k \,/\, \sum_{o=1}^{N}(1-\theta_o^*)$, assigns a share of responsibility for each DMU according to the entire industry's NPLs and how inefficiently the DMU controls NPLs before reduction. The more inefficient a DMU is, the more reduction it should undertake.

2.2. Plan 1

Let $\beta_k = \alpha_k$. Then (6) becomes

$$d_{kn} = \alpha_k b_{kn}\, , \ n = 1, \ldots, N\,; \ k = 1, \ldots, K. \tag{7}$$

The plan simply suggests that each DMU should reduce its undesirable outputs by $\alpha_k b_k$. Because for every DMU and the industry, the reduction rate is the same, this would be considered fair.

2.3. Plan 2

One may argue that, however, Plan 1 is not truly fair, because an efficient DMU and an inefficient DMU assume the same reduction responsibility. To consider efficiency discrepancies, let $\beta_k = 0$; then (6) becomes

$$d_{kn} = \left(\frac{1-\theta_n^*}{\sum_{o=1}^{N}(1-\theta_o^*)}\right)\alpha_k\, B_k\, , \ n = 1, \ldots, N\,; \ k = 1, \ldots, K. \tag{8}$$

This plan suggests that a "relatively" efficient DMU does not need to assume any reduction responsibility. And the more inefficient a DMU is, the more reduction it should undertake. From the viewpoint of individual efficiency, the plan seems fairer than Plan 1.

2.4. Plan 3

It should be noted that the efficiency scores derived from DEA models are based on the concept of relative efficiency, rather than absolute efficiency. For a relatively efficient DMU, it is still possible to reduce its undesirable outputs. This implies that Plan 2 would be impractical. As such, an alternative scheme is to combine Plans 1 and 2.

Let $0 < \beta_k < \alpha_k$. Then giving β_k an arbitrary value within the range, a third plan can be defined.

2.5. Plan 4

We suppose that Plans 1–3 could not be the best plan that we defined earlier. The best plan must be able to maximize industry-level E-NPL. In what follows we will extend Model (5) to develop the desired plan. First, Model (5) is rewritten as the following dual form:

$$Max \ \sum_{j=1}^{J} u_j Y_j - \sum_{i=1}^{I} v_i X_i - N\delta \tag{9.1}$$

$$s.t. \ \sum_{k=1}^{K} s_k B_k = 1; \tag{9.2}$$

$$\sum_{j=1}^{J} u_j y_{jn} - \sum_{i=1}^{I} v_i x_{in} - \sum_{k=1}^{K} s_k b_{kn} - \delta \leq 0, n = 1, \ldots, N; \tag{9.3}$$

$$u_j, v_i, s_k \geq \varepsilon > 0, \ i = 1, \ldots, I; j = 1, \ldots, J; k = 1, \ldots, K; \tag{9.4}$$

$$\delta \text{ is unconstrained in sign}, \tag{9.5}$$

where $u_j, v_i,$ and s_k are unknown weights attached to outputs, inputs, and undesirable outputs, respectively, ε is a non-Archimedean constant, and δ is a variable that allows the underlying technology to be variable returns to scale. Model (9) can be further rearranged as follows:

$$Max \ \frac{\sum_{j=1}^{J} u_j Y_j - \sum_{i=1}^{I} v_i X_i - N\delta}{\sum_{k=1}^{K} s_k B_k} \tag{10.1}$$

$$s.t. \ \frac{\sum_{j=1}^{J} u_j y_{jn} - \sum_{i=1}^{I} v_i x_{in} - \delta}{\sum_{k=1}^{K} s_k b_{kn}} \leq 1, n = 1, \ldots, N; \tag{10.2}$$

$$u_j, v_i, s_k \geq \varepsilon > 0, \ i = 1, \ldots, I; \ j = 1, \ldots, J; \ k = 1, \ldots, K; \tag{10.3}$$

$$\delta \text{ is unconstrained in sign}. \tag{10.4}$$

According to the duality property, the optimal values of the objective functions for Models (5), (9), and (10), i.e. the efficiency measure, are the same, but Model (10) provides a more illuminating exposition of the measure. The efficiency of controlling undesirable

outputs can be defined as a maximum ratio of net production, weighted outputs minus weighted inputs, to weighted undesirable outputs.

Instead of using Eq. (6), we modify Model (9) to determine d_{kn} because the solution of a linear programming problem is an optimal one picked from numerous feasible ones. From a theoretical point of view, Plans 1–3 could be some of the possible solutions of the following programming model, but only the plan derived from the model is optimal. However, Plans 1–3 may be applied in practice, and provide a contrast to the best plan so as to facilitate the understanding of its merits.

We modify Model (9) as follows to determine Plan 4:

$$Max \ \sum_{j=1}^{J} u_j Y_j - \sum_{i=1}^{I} v_i X_i - N\delta \tag{11.1}$$

$$s.t. \ \sum_{k=1}^{K} s_k \left(1-\alpha_k\right) B_k = 1; \tag{11.2}$$

$$\sum_{j=1}^{J} u_j y_{jn} - \sum_{i=1}^{I} v_i x_{in} - \sum_{k=1}^{K} s_k (b_{kn} - d_{kn}) - \delta \leq 0, \ n = 1, \ldots, \ N; \tag{11.3}$$

$$\sum_{n=1}^{N} d_{kn} = \alpha_k B_k, k = 1, \ldots, K; \tag{11.4}$$

$$b_{kn} - d_{kn} > 0, k = 1, \ldots, K; n = 1, \ldots, \ N; \tag{11.5}$$

$$d_{kn} \leq \left(1 - \theta_n^* + \alpha_k\right) b_{kn}, k = 1, \ldots, K; n = 1, \ldots, \ N; \tag{11.6}$$

$$u_j, v_i, s_k \geq \varepsilon > 0, \ i = 1, \ldots, I; j = 1, \ldots, J; k = 1, \ldots, K; \tag{11.7}$$

$$d_{kn} \geq 0, k = 1, \ldots, K; n = 1, \ldots, \ N; \tag{11.8}$$

$$\delta \text{ is unconstrained in sign.} \tag{11.9}$$

Note that in Model (11) DMUs' reductions d_{kn} are unknown decision variables. Constraint (11.4) shows that the sum of DMUs' reductions is equal to the industry-wide reduction. (11.5) is added to avoid the situation that any DMU's reduction is larger than its original volume. Constraint (11.6), where θ_n^* are DMUs' E-NPL before reduction, is added to keep the features of formulas (6)–(8). The constraint sets a maximal value of reduction; the more inefficient before reduction a DMU is, the larger value it is given. The maximal reduction for an efficient DMU is $\alpha_k b_{kn}$.

Model (11) is non-linear. Let $t_{kn} = s_k d_{kn}$. It can be rewritten as the following linear form:

$$Max \ \sum_{j=1}^{J} u_j Y_j - \sum_{i=1}^{I} v_i X_i - N\delta \tag{12.1}$$

$$s.t. \ \sum_{k=1}^{K} s_k \left(1-\alpha_k\right) B_k = 1; \tag{12.2}$$

$$\sum_{j=1}^{J} u_j y_{jn} - \sum_{i=1}^{I} v_i x_{in} - \sum_{k=1}^{K} (s_k b_{kn} - t_{nk}) - \delta \leq 0, \ n = 1, \ldots, \ N; \tag{12.3}$$

$$\sum_{n=1}^{N} t_{kn} = s_k \alpha_k B_k, k = 1,\dots,K; \tag{12.4}$$

$$s_k b_{kn} - t_{kn} > 0 \,, k = 1,\dots,K, n = 1,\dots,\ N; \tag{12.5}$$

$$t_{kn} \le \left(1 - \theta_n^* + \alpha_k\right) s_k b_{kn}, k = 1,\dots,K; n = 1,\dots,\ N; \tag{12.6}$$

$$u_j, v_i, s_k \ge \varepsilon > 0 \,,\ i = 1,\dots,I; j = 1,\dots,J; k = 1,\dots,K; \tag{12.7}$$

$$t_{kn} \ge 0 \,, k = 1,\dots,K, n = 1,\dots,\ N, \tag{12.8}$$

$$\delta \text{ is unconstrained in sign.} \tag{12.9}$$

Using Model (12), we can find optimal values of t_{nk}^* and s_k^*. Let $d_{kn} = t_{kn}^* / s_k^*$. The best reduction plan maximizing industry-wide E-NPL can then be found.

3. Data

The four reduction plans have been computed using data for Taiwan's banking industry. Controlling NPLs has long been an issue in Taiwan. Since the early 1990s, Taiwan's authorities have relaxed regulations and restrictions in exchange for greater participation of private entities. In the banking industry, the liberalization stimulated the development of the financial markets but also encouraged aggressive banking practices. A large number of new banks often engaged in unsound business practices in order to expand their market share. As a result, Taiwan's banking system suffered from an increase in NPLs and a number of financially troubled banks (Yang 2014).

In conducting the proposed models, the first step is the determination of inputs and outputs in banking service. However, in DEA literature, the selection of the inputs and outputs is typically different (Paradi, Zhu 2013). To identify the inputs and outputs, two approaches are commonly used: the production approach and the intermediation approach. In the production approach, a bank is considered to be a firm using its staff, equipment, floor space, etc. to serve its clients, and eventually attracting different types of deposit and loan accounts. Under the intermediation approach, banks are thought of as a financial intermediary between savers and borrowers. One of the most significant differences between the two approaches is the classification of deposits. The production approach regards deposits as outputs, while the intermediation approach considers deposits to be inputs (Holod, Lewis 2011; Paradi, Zhu 2013). Because the goal of reducing NPLs is to address the problem between lenders and borrowers, the intermediation approach is adopted for our case.

The intermediation approach generally posits that deposits, along with labor and physical capital, are inputs, whereas loans and securities are outputs. Yet, granting loans and investing in securities are expected to generate revenue in the end. Therefore, the output used in this study includes revenue and gains (y). The inputs include personnel expenses (x_1), fixed assets (x_2), and deposits (x_3). NPLs are the by-product of the intermediation process, and are regarded as an undesirable output (b).

Taiwan's banking industry currently includes 37 banks. Although Taiwan's authorities have relaxed restrictions on the financial sector, the banking industry is regulated by the Financial Supervisory Commission, which is responsible for the development, supervision, regulation, and examination of financial markets and financial service enterprises. The proposed DEA models are suitable for the case study because they are developed from the viewpoint of the industry-wide development authority or the regulator. We have collected the input and output data from the public information system on the official website of the Financial Supervisory Commission. The data were annual information reported for the year 2015. Table 1 presents the descriptive statistics of the input and output variables.

Table 1. Descriptive statistics of inputs and outputs

Inputs/outputs	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
Personnel expenses (x_1)	5,799	4,760	389	19,814	1.024	0.506
Fixed assets (x_2)	13,347	18,073	555	96,728	3.089	12.245
Deposits (x_3)	933,367	886,416	62,550	3,838,479	1.318	1.608
Revenue and gains (y)	55,673	63,965	1,444	308,051	2.185	5.955
NPLs (b)	1,602	1,626	37	6,805	1.652	2.499

Notes: Inputs and outputs are in millions of NT dollars.

4. Empirical results

Models (1) and (5) have been used to compute bank-level E-NPL and industry-level E-NPL respectively. The results are listed in column 3, Table 2. The computed E-NPL is much lower than we expected. Although 10 banks are relatively efficient in controlling NPLs, the industry-level E-NPL is only 0.301. This is because inefficient banks' E-NPL is extremely low; most of them have a score less than 0.4 (see Fig. 1, the distribution of E-NPL scores). Since the industry-level E-NPL is only 0.301, it is indeed necessary to reduce NPLs in the industry, and the decrease should be massive. Otherwise, efficiency improvement would be insignificant. Figure 1 also shows that banks' E-NPL scores have a bimodal distribution, with some clustered to the efficient end, but with over half being highly inefficient. Intuitively, in this case, one may suggest that the NPL reduction should aim at low E-NPL banks. That is exactly what Plan 2 suggests.

To investigate the suggestion, we conduct a scenario analysis of reducing industry-wide NPLs by 20%; namely the parameter α is given by 0.2. All four reduction plans have been computed. Unfortunately, we find that Plan 2 is infeasible. In viewing Eq. (8), one can see that if a bank's E-NPL is extremely low and the reduction parameter is given with a larger figure, the bank's reduction volume would be considerable. For a bank with modest original NPLs, the reduction target would exceed its original outputs, and as a result this is infeasible. The original NPLs of the sample banks are listed in column 2, Table 2. Take, for instance, Bank 23. Its original NPLs are 175. According to Eq. (8), its reduction target is 306, which is infeasible.

Table 2. Scenario of reducing NPLs by 20%

Bank	Original		Plan 1		Plan 3[*]		Plan 4	
	NPLs	E-NPL	reduction	E-NPL	reduction	E-NPL	reduction	E-NPL
1	5603	1.000	1121	1.000	784	1.000	0	1.000
2	3320	0.133	664	0.133	623	0.137	0	0.133
3	6805	0.113	1361	0.113	1115	0.116	6040	1.000
4	2761	0.378	552	0.378	500	0.397	0	0.364
5	3070	0.201	614	0.201	576	0.212	0	0.201
6	2843	0.189	569	0.189	547	0.198	0	0.189
7	1548	0.228	310	0.229	358	0.244	0	0.228
8	1795	1.000	359	1.000	251	1.000	0	1.000
9	1599	1.000	320	1.000	224	1.000	0	1.000
10	808	0.046	162	0.046	288	0.059	0	0.046
11	1341	0.502	268	0.501	279	0.543	0	0.501
12	1096	0.222	219	0.222	296	0.262	0	0.218
13	175	1.000	35	1.000	25	1.000	35	1.000
14	358	0.252	72	0.253	187	0.455	0	0.243
15	4905	0.055	981	0.055	860	0.053	0	0.055
16	1084	0.121	217	0.121	313	0.135	0	0.120
17	1318	0.059	264	0.060	357	0.047	0	0.059
18	37	1.000	7	1.000	5	1.000	0	1.000
19	129	1.000	26	1.000	18	1.000	0	1.000
20	64	1.000	13	1.000	9	1.000	13	1.000
21	341	0.350	68	0.350	167	0.591	0	0.291
22	935	0.402	187	0.402	240	0.449	0	0.402
23	175	0.211	35	0.214	169	1.000	0	0.211
24	957	0.039	191	0.039	310	0.045	0	0.039
25	229	0.447	46	0.447	133	0.919	172	1.000
26	152	0.569	30	0.570	100	1.000	32	0.718
27	853	0.273	171	0.273	253	0.334	628	1.000
28	884	1.000	177	1.000	124	1.000	177	1.000
29	2143	0.339	429	0.338	421	0.362	1418	1.000
30	1350	0.612	270	0.611	260	0.652	534	0.999
31	753	1.000	151	1.000	105	1.000	0	1.000
32	1655	0.075	331	0.075	401	0.085	0	0.066
33	1138	0.657	228	0.657	222	0.702	0	0.656
34	593	0.331	119	0.332	205	0.436	0	0.327
35	290	0.198	58	0.200	187	0.467	232	1.000
36	1791	1.000	358	1.000	251	1.000	0	1.000
37	4372	0.577	874	0.577	689	0.589	2573	1.000
industry	59270	0.301	11854	0.301	11854	0.317	11854	0.376

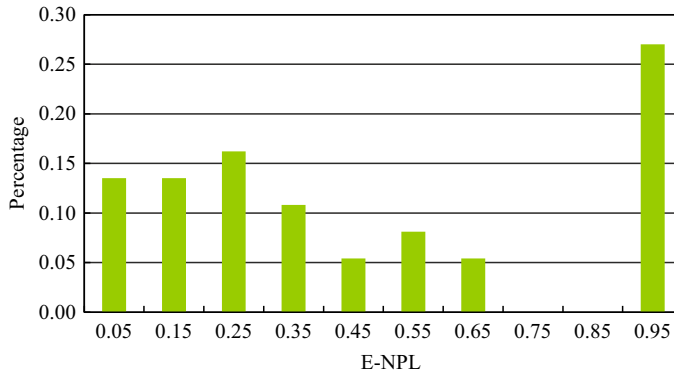*Notes:* * The computed results of Plan 3 are based on $\beta = 0.14$.

Fig. 1. Distribution of E-NPL

We turn to Plan 3, which partially preserves the feature of Plan 2. Because Plan 2 is defined by letting $\beta = 0$, we assign β a new figure as small as possible. However, the plans are also not feasible until $\beta = 0.14$. The resulting reduction for each bank is listed in column 6. Then computing each bank's NPLs after reduction and rerunning Models (1) and (5), we can find new bank-level and industry-level E-NPL when the plan is carried out. The results are listed in column 7. The outcomes show that almost all inefficient banks' E-NPL is improved, with the exception of Banks 15 and 17; efficient banks remain efficient, and industry-level E-NPL is improved as well, from 0.301 to 0.317. However, the extent of improvement is smaller than expected. In a traditional DEA model using a radial input-oriented measure, if an inefficient DMU's inputs are reduced by 20%, the efficiency score would be expected to increase 0.2. The unexpected results can be explained by the structure of Model (1). In the model, when reduction is carried out, all bank's NPLs are changed. Thus both sides of the inequality (1.4) would be changed as well, possibly to the same direction. This would lead to less significant efficiency improvement. However, in a traditional model, reducing an inefficient DMU's undesirable outputs cannot change the left-hand side of the inequality, but will make the observed point closer to the frontier, leading to more significant efficiency improvement.

The phenomenon can be seen more clearly in Plan 1. Using this plan, each bank's reduction is listed in column 4. After reduction, bank-level and industry-level E-NPL are listed in column 5. One can see that banks' E-NPL is almost the same as that before reduction, and industry-level E-NPL stays at 0.301. In other words, the plan cannot improve industry-wide efficiency at all. The results show the limitation of applying a DEA model, since its resulting efficiency is a "relative" concept. When all banks' NPLs are reduced by the same rate, highly efficient banks remain highly efficient, and vice versa. To improve relative efficiency, highly efficient banks should produce more NPLs, while inefficient banks should reduce NPLs. For efficient banks, this does not make sense. Or one may suggest that the reduction should focus only on inefficient banks. Yet, that is exactly the idea of Plan 2, which we have shown to be infeasible above. Therefore, we suggest another one, Plan 4.

Model (12) is used to compute each bank's reduction. The results are listed in column 8. Again, we compute each bank's NPLs after reduction and then rerun Models (1). The resulting E-NPL is listed in column 9. As for industry-level E-NPL, Model (12) has calculated it, or one can rerun Model (5). The results are the same. Through this plan, industry-level E-NPL increases to 0.376, larger than the E-NPL derived from Plans 1 and 3. This is not surprising. As said earlier, the resulting industry-level E-NPL based on this plan is the largest when giving a reduction target. Only 11 banks are assigned the task of reduction. One may expect that these should be the least efficient banks. To our surprise, many extremely inefficient banks, e.g. Banks 10, 15, 17, 24, and 32, are not assigned this task. From a methodological perspective, Plan 4 tries to find a scheme maximizing the ratio of net production (weighted outputs minus weighted inputs) to NPLs at the industry level, which is possibly more sensitive to big banks. We find that those which are not assigned the task of reduction are mostly small banks. The focus is that once a bank is chosen to perform reduction, the reduction would eventually make them become efficient. Besides, an odd result is that a few efficient banks are also assigned the reduction task, but after reduction, they are still efficient. This may be because the production frontier must be adjusted, so the industry-wide efficiency can be maximized. Moreover, efficient banks' reduction is relatively modest compared to inefficient ones; see Banks 13, 20, and 28. One of the reasons is that we have added a constraint, i.e. the inequality (11.6), to make a reduction distinction between efficient and inefficient banks.

To confirm the above empirical findings, we conduct another scenario analysis of reducing the whole industry's NPLs by 40%. The results are shown in Table 3. Using Plan 1, again, both bank-level and industry-level E-NPL scores are almost the same as their original levels. As for Plan 2, due to a larger amount of reduction, it is only natural that the reduction is infeasible. To employ Plan 3, the parameter β must be at least 0.36. The results are listed in columns 6 and 7. Similar to the results of a 20% reduction, the plan can improve E-NPL more than Plan 1. However, the resulting E-NPL is very close to that of the scenario of reducing 20%. Possible reasons are that because β is given by 0.36, very close to $\alpha = 0.4$, its effect upon efficiency improvement is, as a result, similar to Plan 1. Therefore, even though the amount of reduction is larger, the improvement effect is very close to that of the scenario of reducing 20%. If conducting Plan 4, industry-level E-NPL increases to 0.501, again, larger than the results of Plans 1 and 3. To carry out the plan, only 20 banks are needed. And after reduction, almost all these banks will become efficient.

As noted in the introduction section, many previous studies have explored the role of NPLs in efficiency analysis, and found that NPLs have a negative effect on efficiency (Mester 1996; Berger, DeYoung 1997). The argument suggests that the reduction of NPLs can improve a bank's efficiency. Our empirical results agree with this in general. But we have investigated more from a different point of view and obtained following two important cautions when applying the argument. First, past studies mostly explored how NPLs will impact bank efficiency from an individual point of view. The present article, on the other hand, explored how the reduction of NPLs will affect individual

Table 3. Scenario of reducing NPLs by 40%

Bank	Original		Plan 1		Plan 3[*]		Plan 4	
	NPLs	E-NPL	Reduction	E-NPL	Reduction	E-NPL	Reduction	E-NPL
1	5603	1.000	2241	1.000	2017	1.000	0	1.000
2	3320	0.133	1328	0.133	1301	0.138	0	0.133
3	6805	0.113	2722	0.113	2558	0.116	6040	1.000
4	2761	0.378	1104	0.378	1070	0.395	0	0.364
5	3070	0.201	1228	0.201	1203	0.211	2452	1.000
6	2843	0.189	1137	0.189	1122	0.198	387	0.219
7	1548	0.228	619	0.228	651	0.245	0	0.228
8	1795	1.000	718	1.000	646	1.000	0	1.000
9	1599	1.000	640	1.000	576	1.000	0	1.000
10	808	0.046	323	0.045	407	0.059	0	0.022
11	1341	0.502	536	0.502	544	0.539	668	0.999
12	1096	0.222	438	0.221	490	0.257	857	0.999
13	175	1.000	70	1.000	63	1.000	70	1.000
14	358	0.252	143	0.251	220	0.420	0	0.235
15	4905	0.055	1962	0.055	1881	0.054	4637	0.997
16	1084	0.121	434	0.121	498	0.136	953	0.996
17	1318	0.059	527	0.059	589	0.056	1240	0.997
18	37	1.000	15	1.000	13	1.000	0	1.000
19	129	1.000	52	1.000	46	1.000	31	1.000
20	64	1.000	26	1.000	23	1.000	26	1.000
21	341	0.350	136	0.348	202	0.550	0	0.219
22	935	0.402	374	0.402	410	0.449	0	0.402
23	175	0.211	70	0.210	159	1.000	146	1.000
24	957	0.039	383	0.038	462	0.047	0	0.021
25	229	0.447	92	0.447	150	0.831	218	1.000
26	152	0.569	61	0.569	107	1.000	0	0.567
27	853	0.273	341	0.273	396	0.327	628	0.998
28	884	1.000	354	1.000	318	1.000	192	1.000
29	2143	0.339	857	0.339	852	0.359	1418	1.000
30	1350	0.612	540	0.612	533	0.647	534	0.999
31	753	1.000	301	1.000	271	1.000	0	1.000
32	1655	0.075	662	0.075	709	0.084	0	0.043
33	1138	0.657	455	0.657	452	0.697	0	0.656
34	593	0.331	237	0.330	295	0.423	405	1.000
35	290	0.198	116	0.197	202	0.415	233	1.000
36	1791	1.000	716	1.000	645	1.000	0	1.000
37	4372	0.577	1749	0.577	1626	0.588	2573	1.000
industry	59270	0.301	23708	0.301	23708	0.317	23708	0.501

Notes: * The computed results of Plan 3 are based on β = 0.36.

banks' and the whole bank system's efficiency from an industry-wide point of view. From the industry-wide perspective, if all banks reduce their NPLs by the same ratio, the above argument is no longer true. More specifically, in this case, the relative efficiency of individual banks and the whole system is almost the same as their original level. Second, even though the reduction of NPLs is generally helpful in improving industry-wide efficiency, an incorrect reduction plan could make the improvement very insignificant, for example, again, reducing all banks' NPLs by the same ratio.

5. Discussion and implications

Over the last three decades, many economies, including Taiwan, have adopted financial reforms aimed at eliminating different restrictions on the financial sector. However, the financial liberalization may lead to banking crises. One of these crises is the increase in NPLs. To control NPLs and other financial risks, banking systems are still regarded as a regulated industry. For the regulator, the benefit of this study is to help evaluate possible NPL reduction plans. We introduce DEA efficiency estimates, the measure of net production per NPL ratio, to help evaluate NPL reduction plans. Using the measure, the regulator can identify the most efficient plan. Among the possible schemes, we compare four plans. Based on the above scenario analysis, we recommend Plan 4. The plan can improve industry-wide efficiency most. Moreover, different from Plans 1 and 3, the plan just focuses on a finite number of banks, helping identify the key units to improve. This may lower the expenses of reduction. In addition, focusing on limited units can also enable us to implement the reduction plan more easily.

The implications behind the empirical results are that the regulator should devise more incentive measures to control NPLs. Generally, however, regulatory authorities, including Taiwan's Financial Supervisory Commission, use punitive sanctions to control NPLs. For example, according to Taiwan's banking act, if a bank's NPL ratio exceeds 5%, the authority will adopt punitive measures such as issuing an NPL improvement order, restriction on distributions of remuneration to directors and supervisors, restriction on distributions of surplus etc. Punitive sanctions are passive. For those whose NPL ratio does not exceed 5%, the measures lack incentives to motivate them to improve. The implementation of Plan 4, however, requires incentive measures because the target bank's original E-NPL may not be very inefficient.

Besides efficiency, another important issue is what the consequences of the plans with the stability of the financial system are. The suggested approach cannot address this issue in its present form. However, after appropriate revision, we believe that the models can deal with the problem. The key point is to identify the position where the NPLs are riskier, that is, to identify each bank's ability to absorb NPL losses. Then, by dividing banks into several groups according to their ability and revising Model (11) to restrict different reduction targets for each group, we believe that the resulting reduction plan can achieve both stability and efficiency.

Summary and conclusions

Increased NPLs have been a significant problem in many countries all over the world. The present paper has suggested a DEA-based approach for disaggregating an industry-wide NPL reduction target into the aim of each bank so as to maximize banking system efficiency. For comparison, three other plans are also represented. Using a data set from Taiwan's banking industry, the empirical findings have showed that the proposed models can suggest a most efficient reduction plan; the plan focuses on improvement of a finite number of banks, which can be implemented more easily and could possibly lower the expenses of reduction. Possible applications of the findings are that the regulator or policy maker should provide more incentives to control NPLs because the target banks may not be relatively inefficient. Forcing banks to cut their NPLs by the same ratio is not encouraged; it is not at all helpful to improve the relative efficiency of the banks and the industry. Therefore, the present article has successfully provided policy makers an effective quantization approach to develop an efficient NPL reduction scheme, helping address the NPL control problem.

Future studies could extend the proposed approaches in a more practical way. For example, it may be more important to monitor a big bank than a small bank, because a big bank failure is more likely to produce a disastrous effect on the economy. Then, the question is how to incorporate the bank size variance into the model. It will be interesting to see additional research to accommodate this variance. Or, for another example, a bankers' association or regulatory agency may have funding for controlling NPLs. In such a case, future studies can explore how to fairly allocate the funding when designing a reduction plan. Finally, this paper only addresses the NPL reduction issue. There are many other risk factors affecting bank efficiency, e.g. the capital adequacy ratio. Another potential area for future research is to extend this study by covering more risk factors.

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