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Innovative Applications of O.R.

Decomposing banking performance into economic and credit risk efficiencies

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A B S T R A C T

This paper proposes a non-parametric approach of a banking production technology that decomposes performance into economic and credit risk efficiencies. The basis of our approach is to separate the production technology into two sub-technologies. The former is the production of non-interest income and loans from a set of traditional inputs. The latter is attached to the production of interest income from loans where an explicit distinction between good and non-performing loans is introduced. Economic efficiency comes from the production of good outputs, namely interest and non-interest income, while credit risk management efficiency is related to the minimization of the non-performing loans that can be considered as an unintended or bad output. The model is applied to Chinese financial data covering 30 banks from 2005 to 2012 and different scenarios are considered. The results indicate that income could be increased by an average rate of 16% while non-performing loans could be decreased by an average rate of 33%. According to our results, banking managers could strike a balance between economic performance and credit risk management and make more appropriate decisions in line with their preferences.

1. Introduction

The notion of risk plays a key role in banking. Its mismanagement by some of the world's largest financial institutions has led to a global financial crisis that started ten years ago, but whose consequences are still felt today. We revisit the question of risk in banking by formulating the concept of credit risk (in)efficiency and demonstrate how to measure it jointly with the productive (in)efficiency of banks using a nonparametric Data Envelopment Analysis (DEA) model of total banking (in)efficiency.

A number of existing studies approximate risks inherent to banking operations using measures of asset quality, such as non-performing loans. Early papers accounting for problem loans as proxies for risk include Charnes, Cooper, Huang, and Sun (1990) and Berg, Forsund, and Jansen (1992), who use DEA, and Hugues and Mester (1993), Mester (1996) and Berger and DeYoung (1997), who model the technology with a cost function.[1] In their survey of banking efficiency studies, Berger and Humphrey (1997) emphasize the importance of non-performing loans when measuring the productive efficiency of banks. More recently, non-performing assets have been treated as indicators of risk in Barros, Managi, and Matousek (2012), Chiu, Chen, and Bai (2011), Fujii, Managi, and Matousek (2014) and Mamatzakis (2015), Guarda, Rouabah, and Vardanyan (2013), to name just a few among a number of studies approximating banking technologies.[2]

Most of these and other similar studies use problem loans along with conventional inputs and outputs to assess the efficiency

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[1] Berger and DeYoung (1997) formulate several hypotheses with respect to the relationship between nonperforming loans and efficiency and conclude that the quality of banks' assets should be considered in some, but not all cases.

[2] Provisions for loan losses and measures of risky assets have also been used as indicators of risk instead of (or in addition to) non-performing loans to account for credit and operational risk, respectively (Altunbas, Liu, Molyneux, & Seth, 2000; Chang, 1999; Charnes, Cooper, Huang, & Sun, 1990; Drake & Hall, 2003; Drake, Hall, & Simpler, 2009; Mamatzakis, 2015). However, due to data limitations we will focus exclusively on problem loans as a proxy for risk.

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of banks using various modeling techniques. For example, Barros et al. (2012), Colin Glass, McKillop, and Rasaratnam (2010), Fukuyama and Weber (2008), Guarda et al. (2013), Park and Weber (2006), and Fujii et al. (2014) have treated non-performing loans as socially undesirable byproducts or bad outputs, whose decreases at frontier points are not feasible unless accompanied by simultaneous reductions in intended or good outputs as well, assuming the inputs are held constant. This assumption, referred to as the weak disposability of good and bad outputs jointly, has been used in many existing studies to approximate pollution-generating technologies in general (Färe & Grosskopf, 2004; Färe, Grosskopf, Noh, & Weber, 2005).

However, the assumption of a positive association between the good and bad outputs at the frontier of technology could be difficult to justify in the case of banking, where non-performing loans can be avoided provided banks always properly evaluate all loan applications. Murty, Russell, and Levkoff (2012) formulate a "by-production" approach for polluting technologies as a combination of two different sub-technologies – one conventional and the other polluting – thereby addressing the theoretical inconsistencies of the model based on the assumption of weak disposability of the good and bad outputs jointly. Our approach for assessing credit risk (in)efficiency in banking has been inspired both by Murty et al. (2012)) and the network theory of production (Färe & Grosskopf, 1996).

The basis of our approach is to separate the production technology into two sub-technologies. The former corresponds to the production of non-interest income and loans from a set of traditional inputs. The latter is associated with the production of interest income from loans and allows for an explicit distinction between the good and non-performing loans. Hence, the economic efficiency is derived using the production process corresponding to the good outputs, namely interest and non-interest income, while the credit risk (in)efficiency is related to the minimization of non-performing loans, or the unintended output.

In order to model the banking technology, we rely on a so-called profit efficiency model.[3] In our framework, this approach allows us to explicitly model the two banking sub-technologies, where loans are considered an intermediate output in the first sub-technology and subsequently become either an input (for good loans) or a bad output (for non-performing loans) in the second sub-technology. Charnes et al. (1990) were among the first to use such profit-oriented specification, which represents a variation of the asset approach, also referred to as the intermediation approach, introduced by Sealey and Lindley (1977). More recently, various versions of the profit efficiency model have been applied in empirical studies by Avkiran (2011), Avkiran and Thoraneenitiyan (2010), Sturm and Williams (2008), and Drake, Hall, and Simpler (2006), among others. We use Chinese banking data from 2005 to 2012 to provide an empirical illustration of our approach.

Our approach for measuring banking performance represents mainly a threefold contribution. First, we demonstrate how to measure economic and credit risk inefficiency simultaneously. Second, we formulate production sub-technologies, each used to define a particular type of inefficiency, whose intersection allows for such simultaneous measurement. Finally, we measure inefficiency under various scenarios corresponding to the relative importance attributed to the economic versus risk performance of banks by their managers.

The rest of the article is organized as follows. In the next section, we propose a banking production technology incorporating non-performing loan as an undesirable output based on a non-parametric approach; Section 3 applies a Chinese banking data to assess the economic and credit risk performance; the concluding remark and discussion are presented in the last section.

2. Methodology

2.1. Banking production technology with undesirable outputs

We model the production technology for decision making units (DMUs) using an input vector $\mathbf{x} \in \Re_+^n$ used to produce an output vector $\mathbf{y} \in \Re_+^m$. A general banking production possibility set can be defined as follows:

$$T = \left\{ (\mathbf{x}, \mathbf{y}) \in \Re_+^{n+m},\ \mathbf{x} \text{ can produce } \mathbf{y} \right\} \tag{1}$$

Two major approaches usually used to select variables for measuring banking efficiency are the production approach (Bell & Murphy, 1968; Benston, 1965, 1968) and the intermediation approach (Sealey & Lindley, 1977). However, Berger and Humphrey (1997) argued that neither of these approaches can fully capture the dual roles played by banks both as providers of various banking transactions and also as financial intermediaries. Therefore, the profit-oriented approach, which considers both the profits earned and the costs saved in banking operations, gained popularity for selecting variables used to evaluate banking performance (e.g. Avkiran, 2011; Drake et al., 2006; Pasiouras, 2008; Zhu, Wang, Yu, & Wu, 2016). A typical profit-oriented approach treats the cost components, such as the interest and non-interest expenses, as inputs, while treating the revenue components, such as the interest and non-interest income, as outputs.

In this paper, we consider a profit-oriented framework and divide the revenue producing process (T) into two sub-processes, or sub-technologies. In the case of the first sub-technology T_1, banks use inputs $\mathbf{x}$ to produce a single desirable output, or non-interest income (NII), along with a single intermediate output, or total loans (L), which include good loans (GL) and non-performing loans (NPL). Our first sub-technology assumes the banks cannot differentiate between the loans of different quality, since non-performing loans could be avoided if such distinction were possible. In the case of the second sub-technology T_2, two objectives are formulated simultaneously: maximizing the interest income (II) and minimizing the exposure to credit risk. For a given level of total loans, the latter can be achieved via the maximization of good loans together with the minimization of non-performing loans we treat as an undesirable output. Therefore, L is an input, II and GL are desirable outputs, and NPLs are undesirable outputs in T_2, i.e.:[4]

$$\begin{aligned} &T = T_1 \cap T_2 \\ &T_1 = \left\{ (\mathbf{x}, NII, L) \in \Re_+^{n+2}, \mathbf{x} \text{ can produce } NII \text{ and } L \right\} \\ &T_2 = \left\{ (L, II, GL, NPL) \in \Re_+^4, L \text{ can produce } II, GL, NPL \right\} \end{aligned} \tag{2}$$

To estimate the above model we formulate a non-parametric approach that provides an operational definition of the production sets T_1 and T_2 and measures the distance to the frontiers of these sets. We assume that our banking technology satisfied conventional assumptions such as free disposability and convexity. To account for size heterogeneity among banks we assume both of our sub-technologies exhibit variable returns to scale (VRS). Then,

[3] Various approaches to modeling a baking technology have been introduced in the literature. See Berger and Humphrey (1997) or Eken and Kale (2014) for their in-depth discussion.

[4] Even though non-performing loans are our only variable approximating risk inherent to banking, the model can be easily extended to incorporate other types of risk by formulating additional sub-technologies.

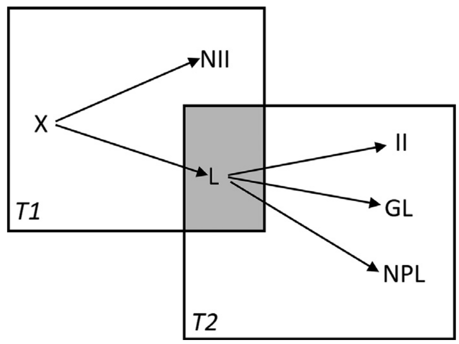

Fig. 1. Banking production process.

T_1 can be defined as:

$$T_1 = \left\{ \begin{array}{l} (\mathbf{x}, NII, L) \in \Re_{+}^{n+2}, \sum_{k=1}^{K} \lambda_k NII_k \geq NII, \sum_{k=1}^{K} \lambda_k L_k \geq L, \\ \sum_{k=1}^{K} \lambda_k x_k^i \leq x^i \forall i = 1, \ldots, n, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \; \forall k = 1, \ldots, K \end{array} \right\}, \tag{3}$$

where λ is a vector of activity variables associated with the sub-technology T_1 (Baumol & Wolfe, 1958; Koopmans, 1951). Similarly, T_2 can be defined as

$$T_2 = \left\{ \begin{array}{l} (L, II, GL, NPL) \in \Re_{+}^{4}, \sum_{k=1}^{K} \sigma_k II_k \geq II, \sum_{k=1}^{K} \sigma_k GL_k \geq GL, \sum_{k=1}^{K} \sigma_k NPL_k \leq NPL, \\ \sum_{k=1}^{K} \sigma_k L_k \leq L, \sum_{k=1}^{K} \sigma_k = 1, \sigma_k \geq 0 \; \forall k = 1, \ldots, K \end{array} \right\}, \tag{4}$$

where σ is a vector of activity variables associated with the sub-technology T_2. In our framework, L is a common element appearing as part of both of our production sub-technologies, implying that the quantity of total loans "produced" by T_1 and "consumed" by T_2 should be equivalent. Thus, we add the following constraint linking the two production processes:

$$\sum_{k=1}^{K} \lambda_k L_k = \sum_{k=1}^{K} \sigma_k L_k \tag{5}$$

The above constraint ensures that the optimal quantity of total loans is equivalent for both sub-technologies. Hence, our banking production technology can be defined in the following fashion:

$$T = \left\{ \begin{array}{l} (\mathbf{x}, L, NII, GL, NPL, II) \in \Re_{+}^{n+5}, \\ \sum_{k=1}^{K} \lambda_k NII_k \geq NII, \sum_{k=1}^{K} \lambda_k L_k \geq L, \sum_{k=1}^{K} \lambda_k x_k^i \leq x^i \forall i = 1, \ldots, n, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \; \forall k = 1, \ldots, K \\ \sum_{k=1}^{K} \sigma_k II_k \geq II, \sum_{k=1}^{K} \sigma_k GL_k \geq GL, \sum_{k=1}^{K} \sigma_k NPL_k \leq NPL, \sum_{k=1}^{K} \sigma_k L_k \leq L, \sum_{k=1}^{K} \sigma_k = 1, \sigma_k \geq 0 \; \forall k = 1, \ldots, K, \\ \sum_{k=1}^{K} \lambda_k L_k = \sum_{k=1}^{K} \sigma_k L_k \end{array} \right\} \tag{6}$$

We summarize and illustrate this production process in Fig. 1. The economic efficiency is obtained from both sub-technologies while the risk efficiency is derived from the second sub-technology only.

We can think of this framework as a version of the by-production model introduced by Murty et al. (2012), which we extend by establishing a formal association between the two sub-technologies and using the Russel directional distance function. However, our approach is also strongly related to a different strand of literature based on network models (Fukuyama & Weber, 2010, 2015, 2017, 2018; Fukuyama & Matousek, 2017, 2018).[5] In particular, similarities can be established in terms of the notion of a sub-technology, the fashion in which two sub-technologies are related, the use of the Russell directional distance function as well as the equivalence between it and some slack-based measures. For example, Fukuyama and Matousek (2018) propose a similar idea of modeling production using two sub-technologies and define the technology T as their intersection, while Fukuyama and Weber (2009) highlight the equivalence of the slack-based measures and the Russell directional distance function. In addition, the way we relate our two by-production sub-technologies using constraint (5) bears certain resemblance to the fashion in which Fukuyama and Weber (2010) accomplish this task in the context of a network-based production model when they rely on the dual mathematical programming program to formulate the corresponding inequality constraint (result (7), p. 401). Our approach is different because it allows us to overlap the sub-technologies directly in the primal space using an equality constraint.

2.2. Estimation of banking efficiency with a directional distance function

A directional distance function can be used to measure the distance from each bank's position inside the technology set T to its corresponding efficient benchmark on this set's frontier. The directional output distance function was proposed by Chambers, Chung, and Färe (1996) and is defined as follows:

$$D_T(\mathbf{x}, \mathbf{y}; \mathbf{g}) = \sup \{\delta \in \Re_{+}, (\mathbf{x}, \mathbf{y} + \delta \mathbf{g}) \in T\}, \tag{7}$$

where δ denotes the increase in outputs necessary to reach the frontier of the banking technology in the direction given by the mapping vector $\mathbf{g}$. It can be interpreted as an inefficiency score, where $\delta = 0$ signals zero inefficiency and implies that the corresponding bank serves as a production benchmark.

While δ is a unique scalar as defined in (7), our approach allows us to distinguish between several components related to the economic and risk inefficiency. We therefore introduce $\delta = (\delta_1, \delta_2, \delta_3)$ as a vector of inefficiency scores and $\mathbf{w} = (w_{econ}, w_{econ}, w_{risk})$ as an exogenous vector of weights, which specify the relative preferences with respect to the economic versus credit risk management performance. The economic inefficiency score is decomposed into two different components, δ_1 and δ_2, which measure inefficiency corresponding to (or shortfalls in) NII and II, respectively, while δ_3 measures the credit risk inefficiency. These inefficiency scores are consequently weighted by the components of the vector $\mathbf{w}$ in the objective function, similar to the approach proposed by Athanassopoulos (1995) in the context of the Goal programming and Data Envelopment Analysis models. For example, we can assign a unique weight w_{econ} to our intended economic outputs NII and II and a different weight, e.g. w_{risk}, to the undesirable output NPL, which approximates credit risk. By adjusting these weights, we can simulate various preferences of bank managers who must face performance tradeoffs between profits and risk.

Furthermore, we assume our direction vector is defined as $\mathbf{g} = (g_{TI}, g_{TI}, g_{NPL}) = (TI, TI, NPL)$, where g_{TI}– the observed total income, or the sum of NII and II – is the direction corresponding to the economic inefficiency score. Similarly, we assume g_{NPL} is the actual value of our proxy for credit risk, or NPL. Hence, our economic inefficiency score is measured as the percentage increase

[5] We thank a reviewer for pointing out this connection.

in total income required to reach the production frontier in the direction g_{TI}, since both δ_1 and δ_2 are related to g_{TI}, whereas δ_3 measures credit risk inefficiency defined as the reduction in *NPL* necessary to attain the frontier in the direction g_{NPL}. Since total loans are defined as the sum of good and non-performing loans, the decrease in *NPL*, or $\delta_3 g_{NPL}$, must be equivalent to the increase in good loans.

Hence, the directional distance function in (7) can be modified as follows:

$$D_T(\mathbf{x},\mathbf{y};\mathbf{w},\mathbf{g}) = \sup\{\mathbf{w}\delta \in \Re : (\mathbf{x},\mathbf{y}+\delta\mathbf{g}) \in T\} \tag{8}$$

The directional distance function in (8) is related to the slack-based inefficiency measure described in Fukuyama and Weber (2009), who demonstrate how the equivalence between the directional distance function and a slack-based measure can be established using an appropriate direction vector and a suitable variable transformation.[6]

Finally, for any DMU *k'*, our directional output distance function can be estimated using the following linear programming problem:

$$D_T(\mathbf{x_{k'}}\mathbf{y_{k'}};\mathbf{w},\mathbf{g_{k'}}) = \underset{\delta_1,\delta_2,\delta_3,\lambda,\sigma}{Max}\; w_{econ}(\delta_1+\delta_2) + w_{risk}\delta_3$$

$$\begin{aligned}
&s.t. \sum_{k=1}^{K}\lambda_k NII_k \geq NII_{k'} + \delta_1 g_{TI}\\
&\sum_{k=1}^{K}\lambda_k L_k \geq L_{k'}\\
&\sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n \forall n = 1,2\\
&\sum_{k=1}^{K}\lambda_k = 1\\
&\sum_{k=1}^{K}\sigma_k II_k \geq II_{k'} + \delta_2 g_{TI}\\
&\sum_{k=1}^{K}\sigma_k GL_k \geq GL_{k'} + \delta_3 g_{NPL}\\
&\sum_{k=1}^{K}\sigma_k NPL_k \leq NPL_{k'} - \delta_3 g_{NPL}\\
&\sum_{k=1}^{K}\sigma_k L_k \leq L_{k'}\\
&\sum_{k=1}^{K}\sigma_k = 1\\
&\sum_{k=1}^{K}\lambda_k L_k = \sum_{k=1}^{K}\sigma_k L_k\\
&\lambda_k \geq 0\ \forall k = 1,\ldots,K\\
&\sigma_k \geq 0\ \forall k = 1,\ldots,K
\end{aligned} \tag{LP1}$$

We conclude the chapter with some remarks about the above problem. First, since the first sub-technology does not seek to optimize the level of loans, in T_1 the economic inefficiency score is derived from the bank's ability to generate non-interest income from its current expenses, meaning the economic performance does not depend on the amount of loans held by the bank. In T_2, the economic efficiency is obtained by maximizing the interest income whatever the composition of the loan portfolio for a given level of loans in the current year. In other words, our model assumes the economic efficiency is related to the current year of operation and the risk performance is based on the minimization of non-performing loans in the current loan portfolio. However, in reality a bank's risk performance is likely to depend at least in part on its past credit policy as well, implying our model is clearly static in nature. Unfortunately, we are unable take the specificities of the *NPL*-generating process into account in our model by, for example, including the lagged values of *NPL*s, as this would require much more detailed data than we have under our disposal. However, such linking of loan portfolios over time could be an important extension of our approach, especially when used with relatively recent data, in light of the recommendations for a harmonized and uniform measurement of *NPLs* outlined in the Basel III accords (BCBS, 2017). For example, regulators can rely on both the current and future level of *NPLs* when testing banks' soundness using specialized asset quality reviews and/or stress tests.[7]

Table 1
Descriptive statistics: 2005–2012.

Variable	Unit	Mean	S. D.	Min	Max	C.V.
IE	Million CNY_{2004}	24,956	42,242	265	238,676	1.69
NIE	Million CNY_{2004}	15,654	28,100	181	128,600	1.80
II	Million CNY_{2004}	60,809	106,454	507	567,179	1.75
NII	Million CNY_{2004}	7893	17,449	1	87,007	2.21
NPL	Million CNY_{2004}	22,522	84,409	64	756,190	3.75
L	Million CNY_{2004}	768,944	1,354,571	8710	6,747,535	1.76

Note: S.D. = standard deviation; C.V.= coefficient variation.

3. Empirical application of Chinese banking

3.1. Chinese banking data

In our empirical application, we rely on a sample of 30 Chinese commercial banks representing 240 observations spanning 8 years from 2005 to 2012. The summary statistics of the sample are given in Table 1. The banks are divided into three categories we mention in the Appendix along with the names of the banks, i.e. the state-owned commercial banks, the joint-stock commercial banks, and the city commercial banks, allowing us to distinguish among different banking technologies. All of the data come from the Bankscope database, and the variables are expressed Chinese yuan with 2004 as the base year (CNY_{2004}).

We assume the input vector **x** consists of interest expenses (*IE*) and non-interest expenses (*NIE*). Furthermore, recall that total loans (*L*) are an intermediate output, interest income (*II*) and non-interest income (*NII*) are good outputs, and non-performing loans (*NPL*) are bad outputs. Good loans (*GL*) are obtained as the difference between *L* and *NPL*. A bank's capacity to loan funds depends on its level of deposits and the reserve rate, determined by the central bank (People's Bank of China) and the China Banking and Insurance Regulatory Commission. A profit-maximizing bank will always attempt to lend as much of its deposit holdings as possible. Hence, we assume that banks do not hold any extra reserves and loan as much of their funds as they are allowed to. Table 1 contains the descriptive statistics corresponding to these variables for all three types of banks. Looking at the last column, we note a significant fluctuation in *NPL*, whose coefficient of variation equals 3.75. Fig. 2 shows that the share of *NPL* among total loans has steadily decreased during the sample period for all three categories of banks and that the state-owned commercial banks have a higher share of *NPL* compared to the other two types of banks.

[6] We would like to thank one of the referees for pointing out this equivalence.

[7] See for example Baudino and Yun (2017) for an in-depth discussion of *NPLs* in the context of Basel III accords.

Table 2
Weight on economic and risk efficiencies for scenarios.

Scenario	W_{econ} (%)	W_{risk} (%)
1	100	0
2	90	10
3	80	20
4	70	30
5	60	40
6	50	50
7	40	60
8	30	70
9	20	80
10	10	90
11	0	100

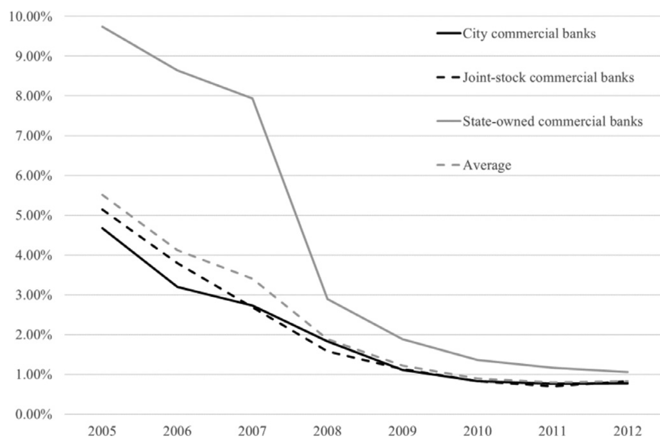

Fig. 2. Evolution of the share of non-performing loans.

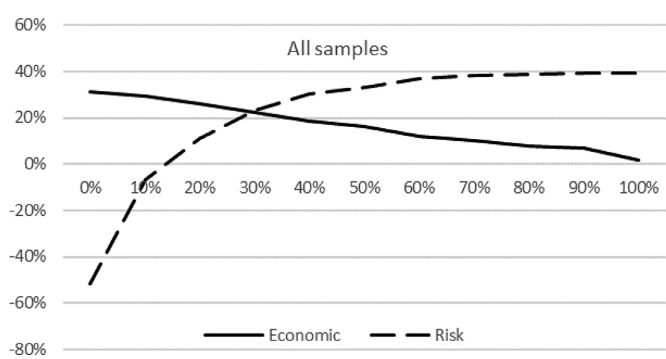

Fig. 3. The tradeoff between economic and risk performances.
Note: Potential improvement in economic or risk performance is plotted on the vertical axis and the weight corresponding to risk control is on the horizontal axis.

To operationalize our problem, we need to choose the fashion in which to partition the weights appearing in the objective function of LP1. These weights can be interpreted as different preferences banks may have with respect to the two dimensions of performance described earlier, i.e. the economic and risk performance. Although a partitioning such as w_{econ}=w_{risk}=50% is an obvious choice, many other combinations are also possible. Thus, we consider eleven such combinations of weights corresponding to the economic versus credit risk performance, which are described in Table 2.

3.2. Empirical results

We first look at the results corresponding to the average economic and risk performance for each of the eleven scenarios and the entire sample, summarized in Table 3 and Fig. 3. Results clearly

Table 3
Average economic and risk inefficiencies for scenarios.

Scenario	Economic inefficiency $\delta_1 + \delta_2$(%)	Credit risk inefficiency δ_3(%)
1	31	−52
2	29	−7
3	26	11
4	22	23
5	19	31
6	16	33
7	12	37
8	10	38
9	8	39
10	7	39
11	2	39

Note: Economic inefficiency indicates possible improvement for interest and non-interest income, i.e. if $\delta_1 + \delta_2$ is 10% then total income can be increased by the same amount. Credit risk management inefficiency measures possible reduction in non-performing loans, i.e. if δ_3 is 10% then non-performing loans can be reduced by the same amount. Negative values of δ_3 imply the corresponding bank is above the frontier of technology.

vary under alternative scenarios. For example, a rise in the weight attributed to risk performance is associated with a gradual reduction in non-performing loans, which tops at 39% at the frontier of the technology when only credit risk efficiency is assumed to matter, i.e. w_{risk}=100%. On the contrary, a decline in w_{risk} culminates in a 52% increase in bad loans when only economic efficiency matters to bank managers. Changes in the weight associated with credit risk and control also influence the corresponding economic inefficiency, as the average potential gain in the interest and non-interest income grows from an average of 31% when banks are assumed to target profits with no concern for an increase in bad loans to an average of just 2% when all of the efforts are directed at controlling risk.

Fig. 3 provides a summary of this relationship by illustrating how policies directed at controlling risk, i.e. banking regulation, may cause a sharp decline in income but help reduce non-performing loans. As expected, decisions to allocate fewer resources to the screening of loan applications – a scenario consistent with relatively high values of $\mathbf{w}_{econ}$ and low values of $\mathbf{w}_{risk}$ – help increase profitability but come at the expense of a simultaneous increase in problem loans for the efficient banks. Such willingness to accept more non-performing assets is consistent with these banks' treatment of credit risk performance as being relatively unimportant under such scenarios. Furthermore, looking at the patterns of change in the economic versus credit risk performance, we can see that while the economic inefficiency decreases at a roughly constant rate as progressively more importance is attributed to the management of risk, the associated rate of reduction in *NPLs* is clearly decreasing. In other words, banks find it easier to avoid non-performing assets as the risk performance is only starting to matter than when $\mathbf{w}_{risk}$ is already relatively high, as risk in banking – measured using *NPLs* or otherwise – simply cannot be eliminated completely.

In Fig. 4, we present the tradeoff between economic performance and credit risk separately for each bank type. While these graphs are comparable to the pattern above, there appear to be important differences among the three groups we consider. Looking first at the state-owned commercial banks (SOCBs), we note that economic inefficiency, which can be interpreted as potential increase in profitability, is decreasing from 11% to 5% on average, while risk inefficiency, which implies a possible reduction in non-performing loans, is simultaneously increasing from 0% to 20% as the share of weight attributed to risk performance grows from 0%

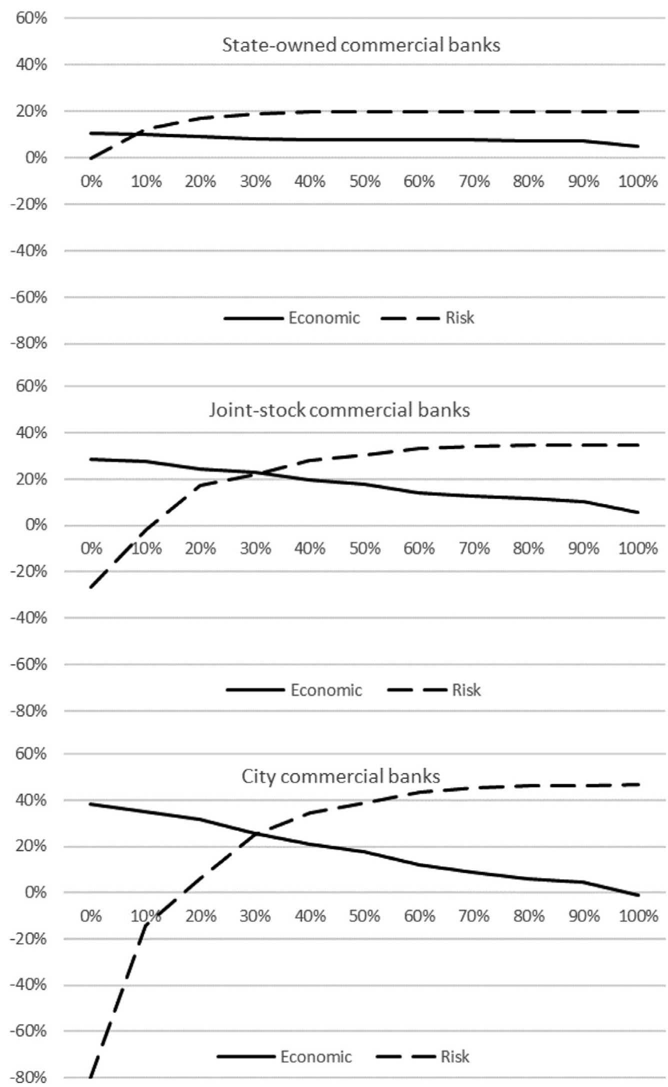

Fig. 4. The tradeoff between economic and risk performance for various types of banks.
Note: Potential improvement in economic or risk performance is plotted on the vertical axis and the weight corresponding to risk control is on the horizontal axis.

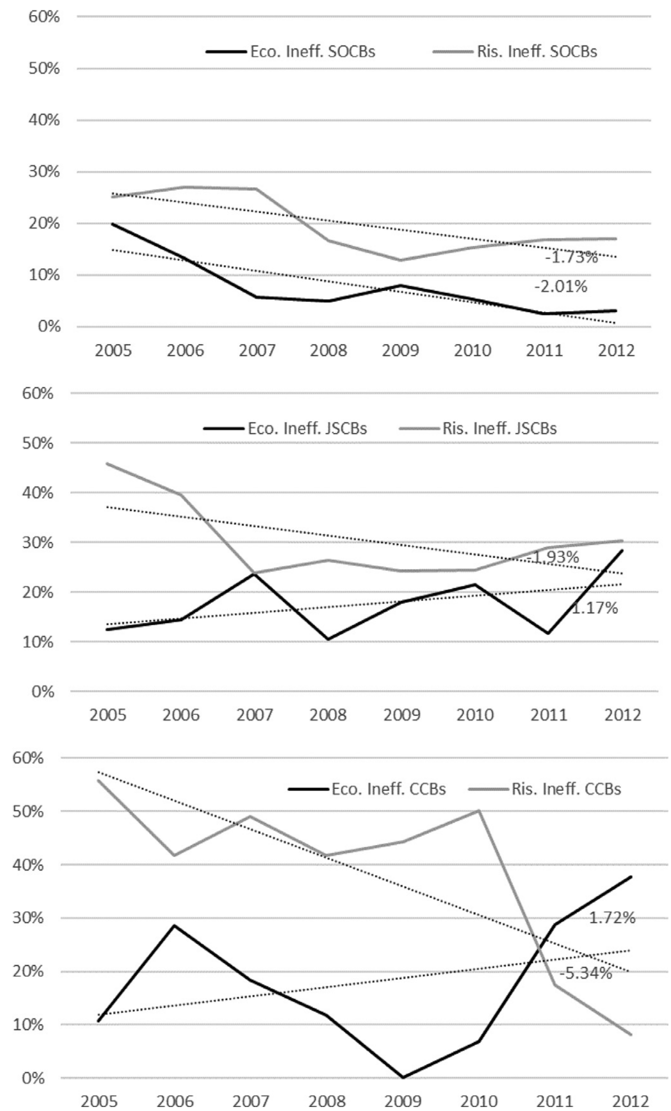

Fig. 5. Evolution of the economic and risk performance assuming $w_{econ}=w_{risk}=50\%$.

to 100%. Also, we can see that the SOCBs experience no meaningful increase in credit risk inefficiency beyond the scenario where $w_{risk}=30\%$ and $w_{econ}=70\%$, while the associated economic inefficiency gains remain roughly constant at approximately 10% of total income regardless of how one partitions the preferences for the two types of performance. Considering the SOCBs have historically had a relatively large share of problem loans on their books (Fig. 2), making it at least possible for these institutions to have improved their credit risk performance in a more meaningful fashion, this result could be explained by the role the SOCBs play in the Chinese economy as key providers of credit. Bearing in mind their status of state-owned credit institutions, it is possible the SOCBs are expected to provide loans to a relatively wide array of economic agents, including those possessing less-than perfect credit rating, even when credit risk performance matters a lot to these banks.

Furthermore, we see that decisions to assign any particular weight can have a significant impact on the economic performance and the management of risk in the case of the joint-stock commercial banks (JSCBs) and the city commercial banks (CCBs) as well, and that the sensitivity to changes in w_{risk} and w_{econ} is clearly not the same compared to the SOCBs. For example, the relatively steep curves corresponding to CCBs suggest they may be the most sensitive to the various credit risk-related strategies.

We finally consider one of the possible scenarios by partitioning the preferences in a particular fashion, i.e. $w_{\text{econ}}=w_{\text{risk}}=50\%$, and summarize the results in Fig. 5. While the economic performance of both the JSCBs and CCBs has worsened over time at an average annual rate of 1.17% and 1.72%, respectively, the SOCBs' inefficiency has declined at 2.01% per year, suggesting the crisis might have had a bigger impact on the JSCBs and CCBs compared to the state-owned banks. This result is hardly surprising, considering the status of the SOCBs as relatively mature financial institutions playing a leading role in the Chinese banking industry, and may be attributed to the effectiveness of the reforms implemented in the Chinese banking sector since 2003, such as the changes in the shareholding system (Dong, Firth, Hou, & Yang, 2016; Jiang, Yao, & Feng, 2013; Zhu, Wu, Wang, & Yu, 2019).

As far as the risk performance is concerned, the three types of banks appear to be catching up with one another as the risk inefficiency scores are changing at the average annual rate of −1.73%, −1.93%, and −5.34% for the SOCBs, JSCBs, and CCBs, respectively. These improvements are very much in line with the overall progress in the performance of banks cited in a number of recent studies of the Chinese banking sector (Matthews, 2013; Wang, Huang, Wu, & Liu, 2014; Zhu et al., 2019). Upon closer examination, we can see the largest drop in credit risk inefficiency in the post-crisis era has occurred among the CCBs – assuming the two types of performance are weighted equally – suggesting the regulatory measures put in place to tackle exposure to credit risk might have benefited these institutions the most. Looking at the bottom two graphs, we also note the relatively high volatility in the performance of the JSCBs and CCBs, also reported by Zhang, Cai, Dickinson, and Kutan (2016) and Zhu et al. (2019), which implies these banks could continue benefiting from the policies implemented by the China Banking and Insurance Regulatory Commission aimed at further stabilizing the performance of the country's financial sector.

4. Conclusion and directions for the future

The notion of risk control plays a key role in banking. Its mismanagement by some of the world's largest financial institutions has led to a global financial crisis that started ten years ago, but whose consequences are still felt today. However, modeling credit risk efficiency in the same way as pollution-generating technologies, which assumes a positive association between the intended and unintended outputs at the frontier of technology, could be difficult to justify in the case of banking.

We depart from this approach by introducing a different model based on two sub-technologies. Loans are considered an intermediate output in the first sub-technology before being decomposed into good and non-performing loans in the second sub-technology, where the former are maximized and the latter are minimized. Such approach allows us to define and simultaneously measure both credit risk inefficiency and the economic performance of banks. We provide an empirical illustration of our model using a sample of 30 Chinese banks from 2005 to 2012 and consider various strategies banks may pursue to distinguish between the different policy objectives corresponding to economic performance and risk.

Our results indicate that banks can increase their total income at an average rate of 16% while simultaneously decreasing their non-performing loans at an average rate of 33% when preferences for economic and risk performance are weighted equally. Our model can accommodate alternative weighing schemes for these preferences, presenting researchers with more flexibility in modelling the constantly evolving economic (e.g. the continued development of China's economy) and financial (e.g. the establishment of financial risk-monitoring system) conditions. Bank managers may find it useful to take advantage of this flexibility when attempting to strike a balance between economic performance and risk as they try to meet their profitability targets. Another key takeaway from our study is the relatively low estimated credit risk inefficiency of the state-owned banks, which we observe regardless of their relatively high stock of problem assets before, during and immediately following the crisis. We surmise this could possibly be due to directives to meet the demand for funds from borrowers with different levels of credit risk appetite, which these banks likely receive from the government. Finally, we find the economic and credit risk inefficiency appear to be moving in the opposite directions most of the time. Our results suggest improving credit risk efficiency has required a simultaneous rise in economic inefficiency among the joint-stock commercial banks and the city commercial banks, underlying the importance of recognizing this trade-off when measuring the performance of financial institutions.

We conclude by suggesting that future efforts devoted to the simultaneous measurement of economic and credit inefficiency should account for the additional proxies for credit, market, and/or operational risk inherent to banking, which we were unable to include in the present study due to data limitations. Also, the idea of approximating a production process using two technologies can be further extended by including additional sub-technologies, allowing researchers to better tailor their models to the specificities of unconventional production processes.

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Appendix

Type	Bank name
State-owned commercial banks	China Agricultural Bank, Bank of China, Industrial and Commercial Bank of China, and China Construction Bank
Joint-stock commercial banks	China CITIC Bank, China Bank of Communications, China Everbright Bank, Industrial Bank, Hua Xia Bank, China Guangfa Bank, China Merchants Bank, China Minsheng Bank, Shanghai Pudong Development Bank, Shenzhen Development Bank
City commercial banks	Bank of Shanghai, Bank of Dongguan, Bank of Beijing, Bank of Nanjing, Bank of Harbin, Bank of Dalian, Bank of Tianjin, Bank of Ningbo, Bank of Hengfeng, Bank of Hangzhou, Bank of Hankou, Bank of Hebei, Bank of Zheshang, Bank of Wenzhou, Bank of Jinzhou, Bank of Qingdao

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