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Abstract:

This paper proposes a novel non-parametric approach of a banking production technology that decomposes performance into economic and risk management 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 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 risk-management and make more appropriate decisions in line with their preferences.

Keywords: Data Envelopment Analysis; Risk management; Economic efficiency; Banking performance; Non-performing loans.

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Highlights

1. We propose a novel non-parametric approach to evaluate bank performance;
2. Bank performance is decomposed into economic and risk management efficiencies;
3. The proposed model is applied to Chinese financial dataset over 2005-2012;
4. Various strategies are considered to distinguish among different policy objectives.

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 almost ten years ago, but whose consequences are still felt today. Nevertheless, to our knowledge the question of efficiency with which risk in banking can be managed – i.e. risk management (in)efficiency – has received no attention in the literature, despite a plethora of studies acknowledging the importance of accounting for risk when approximating a banking technology. We attempt to fill this gap by formulating a nonparametric Data Envelopment Analysis (DEA) model of banking (in)efficiency that can be decomposed into pure economic and risk management (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 et al. (1990) and Berg et al. (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 Chiu et al. (2011), Barros et al. (2012), Guarda et al. (2013), Fujii et al. (2014) and Mamatzakis (2015), 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 of banks using various modeling techniques. For

[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 have also been used as a measure of risk instead of (or in addition to) nonperforming loans. See, for example, Charnes et al. (1990), Chang (1999), Altunbas et al. (2000), Drake and Hall (2003), Drake et al. (2009), and Mamatzakis (2015).

example, Park and Weber (2006), Fukuyama and Weber (2008), Colin Glass et al. (2010), Barros et al. (2012), Guarda et al. (2013), 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 and Grosskopf (2004), Färe et al. (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 et al. (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 risk management (in)efficiency in banking has been inspired both by Murty at al. (2012) and the network theory of production [Färe and Grosskopf (1996)].

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 risk-management efficiency is related to the minimization of the non-performing loans that can be considered a bad 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 a good output in the first sub-technology and 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 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 et al. (2006), among others. We use Chinese banking data from 2005 to 2012 to provide an empirical illustration of our approach.

The rest of the article is organized as follows. In the next section, we propose a novel 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 risk management 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 **x** used to produce an output vector **y**. A general banking production possibility set can be defined as follows:

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

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

Berger and Humphrey (1997) introduced two major approaches, namely the production and the intermediation approach, to select variables for measuring banking efficiency, but they also argued that neither of them can fully capture the dual roles of the financial sector. 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. Drake et al. 2006; Pasiouras, 2008; Avkiran, 2011; Zhu et al., 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 technology T_1, banks use inputs $\boldsymbol{x}$ 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). In the case of the second technology T_2, GL are assumed to produce a socially desirable output interest income (II), while NPL are treated as an undesirable output.

$$\begin{aligned} T &= T_1 \cap T_2 \\ T_1 &= \left\{ x \text{ can produce } NII \text{ and } L \right\} \quad (2) \\ T_2 &= \left\{ L \text{ can produce } II \right\} \end{aligned}$$

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 variable returns to scale (VRS) for both of our sub-technologies. Then, T_1 can be defined as:

$$T_1 = \left\{ (x, NII, L) \in \Re_+, \sum_{k=1}^{K} \lambda_k NII_k \geq NII, \sum_{k=1}^{K} \lambda_k L_k = L, \sum_{k=1}^{K} \lambda_k x_k^n \leq x, \right.$$
$$\left. \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \quad \forall k = 1,\ldots,K \right\} \tag{3}$$

where λ is a vector of activity variables associated with the sub-technology T_1 (Koopmans, 1951; Baumol, 1958). In our approach, since loans cannot be considered freely disposable due to certain legal constraints, we resort to an equality sign in the definition of T_1 instead an inequality sign that is usually used in similar cases. Similarly, T_2 can be defined as

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

where σ is a vector of activity variables associated with the sub-technology T_2. In the framework of our profit-oriented efficiency model, 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. Since banks face a tradeoff between the production of non-interest and interest income, we add the following constraint linking the processes resulting in the production of these two types of income:

$$\sum_{k=1}^{K} \lambda_k L_k = \sum_{k=1}^{K} \sigma_k L_k \Leftrightarrow \sum_{k=1}^{K} \lambda_k (GL_k + NPL_k) = \sum_{k=1}^{K} \sigma_k (GL_k + NPL_k) \tag{5}$$

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:

$$T = \{ (x, NII, L, GL, NPL, II) \in \Re_{+},$$
$$\sum_{k=1}^{K} \lambda_k NII_k \geq NII, \sum_{k=1}^{K} \lambda_k x_k^n \leq x, \sum_{k=1}^{K} \lambda_k L_k = L, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \quad \forall k$$
$$\sum_{k=1}^{K} \sigma_k II_k \geq II, \sum_{k=1}^{K} \sigma_k GL_k = GL, \sum_{k=1}^{K} \sigma_k NPL_k = NPL, \sum_{k=1}^{K} \sigma_k = 1, \sigma_k \geq 0 \quad \forall k$$
$$\sum_{k=1}^{K} \lambda_k L_k = \sum_{k=1}^{K} \sigma_k L_k \}$$

(6)

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 et al. (1996) and is defined as follows:

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

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

While δ is a unique scalar as defined in Eq 7, our approach allows us to distinguish between its two components, i.e. the economic and risk inefficiency. 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 risk. By adjusting these weights, we can simulate different preferences of bank managers who must face the tradeoff between economic revenue and risk. The corresponding directional distance function can be defined as follows:

$$D_T(\mathbf{x_{k'}} \mathbf{y_{k'}}; \mathbf{w}, \mathbf{g_{k'}}) = \sup\left\{\mathbf{w}\delta \in \Re : (\mathbf{x}, \mathbf{y} + \delta\mathbf{g}) \in T\right\} \tag{8}$$

where $\mathbf{w} = \left\{w_{econ}, w_{risk}\right\}$ specifies different policy objectives for banks. Furthermore, we assume that our direction vector **g** consists of two sub-vectors – g_{TI}, or the common direction based on the observed total income *TI*, defined as the sum of *NII* and *II* we use to measure economic performance, and g_{NPL}, which corresponds to our proxy for risk and is based on non-performing loans *NPL*, i.e. $\mathbf{g} = (g_{TI}; g_{NPL}) = (NII + II; NPL)$. The economic efficiency score is also decomposed into different components, or δ_1 and δ_2, which measure inefficiency for *NII* and *II*, respectively. Our economic efficiency score is measured in terms of the percentage of total income, since both δ_1 and δ_2 are related to g_{TI} as demonstrated below. Finally, δ_3 measures risk management inefficiency defined as the reduction in *NPL* necessary to attain the production 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 *GL*.

In our empirical application, we use Chinese banking data from 2005 to 2012. 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 Banking 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. Finally, our directional output distance function can be estimated using the following linear programming problem:

$$
\begin{aligned}
& D_T(\mathbf{x}_{\mathbf{k}'}\mathbf{y}_{\mathbf{k}'};\mathbf{w},\mathbf{g}_{\mathbf{k}'}) = \underset{\delta_1,\delta_2,\delta_3,\lambda,\sigma}{Max} \quad w_{econ}(\delta_1+\delta_2)+w_{risk}\delta_3 \\
s.t.\ & \sum_{k=1}^{K}\lambda_k NII_k \geq NII_{k'}+\delta_1 g_{TI} \\
& \sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n \quad \forall n=1,2 \\
& \sum_{k=1}^{K}\lambda_k L_k = L_{k'} \\
& \sum_{k=1}^{K}\sigma_k II_k \geq II_{k'}+\delta_2 g_{TI} \\
& \sum_{k=1}^{K}\sigma_k NPL_k = NPL_{k'}-\delta_3 g_{NPL} \\
& \sum_{k=1}^{K}\sigma_k GL_k = GL_{k'}+\delta_3 g_{NPL} \\
& \sum_{k=1}^{K}\lambda_k L_k = \sum_{k=1}^{K}\sigma_k L_k \\
& \sum_{k=1}^{K}\lambda_k = 1 \\
& \sum_{k=1}^{K}\sigma_k = 1 \qquad\qquad \text{(LP1)} \\
& \lambda_k \geq 0 \quad \forall k=1,\dots,K \\
& \sigma_k \geq 0 \quad \forall k=1,\dots,K
\end{aligned}
$$

3. Empirical application of Chinese banking

3.1 Chinese banking data

Our data sample contains 240 observations spanning 8 years from 2005 to 2012 corresponding to 30 Chinese commercial banks we describe in the appendix. The banks are divided into three categories, i.e. state-owned commercial banks, joint-stock commercial banks, and 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 that interest expenses (*IE*) and non-interest expenses (*NIE*) are inputs, 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*. 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. Figure 1 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.

Table 1 about here

Figure 1 about here

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 risk management performance, which are described in Table 2.

Table 2 about here

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 Figure 2. Results clearly 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 risk management 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 risk management 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. Figure 2 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.

Table 3 about here

Figure 2 about here

In Figure 3, we present the tradeoff between economic performance and risk management separately for each bank type. Looking first at the state-owned commercial banks (SOCBs), we note that economic inefficiency, which can be interpreted as potential profitability, is decreasing from 11% to 5% on average, while risk inefficiency, which implies a possible reduction of non-performing loans, is simultaneously increasing from 0% to 20% as the share of weight attributed to risk performance grows from 0% to 100%. Furthermore, we see that decisions to assign any particular weigh can have a significant impact on the economic performance and management of risk in the case of joint-stock commercial banks (JSCBs) and city commercial banks (CCBs) as well, and that the degree of sensitivity in the economic and risk performance clearly varies by bank type. For example, the relatively steep curves corresponding to city commercial banks suggest they may be the most sensitive to the various risk management strategies.

Figure 3 about here

We finally consider one of the possible scenarios by assigning particular weights to the economic versus risk performance, i.e. $w_{\text{econ}}=w_{\text{risk}}=50\%$, and summarize the results in Figure 4. While the economic performance of both JSCBs and CCBs improves over time at the average annual rate of 1.17% and 1.72%, respectively, SOCBs display a negative average growth rate of -2.01% per year, suggesting that JSCBs and CCBs have had more opportunities to increase their profitability compared to SOCBs. This result is hardly surprising, considering the status of the SOCBs as relatively mature financial institutions playing a leader role in the Chinese banking industry. As far as risk performance is concerned, the three types of banks appear to be catching up with one another as the risk inefficiency scores are decreasing at the average annual rate of -1.73%, -1.93%, and -5.34% for SOCBs, JSCBs, and CCBs, respectively.

Figure 4 about here

4. Conclusion and discussion

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 almost ten years ago, but whose consequences are still felt today. However, modeling risk management efficiency in the same way as pollution-generating technologies, which assumes a positive association between the good and bad outputs at the frontier of technology, could be difficult to justify in the case of banking.

We depart from this approach by introducing a new 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 risk management 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 different policy objectives concerning economic performance and risk. For example, our results indicate that banks can increase their non-interest and interest 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 also 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. Finally, bank managers can take advantage of this flexibility when attempting to strike a balance between economic performance and risk as they try to meet their profitability targets.

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Table 1 Descriptive statistics: 2005-2012

Variable	Unit	Mean	S. D.	Min	Max	C.V.
IE	Million CNY_{2004}	24956	42242	265	238676	1.69
NIE	Million CNY_{2004}	15654	28100	181	128600	1.80
II	Million CNY_{2004}	60809	106454	507	567179	1.75
NII	Million CNY_{2004}	7893	17449	1	87007	2.21
NPL	Million CNY_{2004}	22522	84409	64	756190	3.75
L	Million CNY_{2004}	768944	1354571	8710	6747535	1.76

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

Table 2 Weight on economic and risk efficiencies for scenarios

Scenario	$\mathbf{W_{econ}}$	$\mathbf{W_{risk}}$
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%

Table 3 Average economic and risk inefficiencies for scenarios

Scenario	Economic inefficiency $\delta_1 + \delta_2$	Risk-management 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. 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.

Figure 1 Evolution of the share of non-performing loans

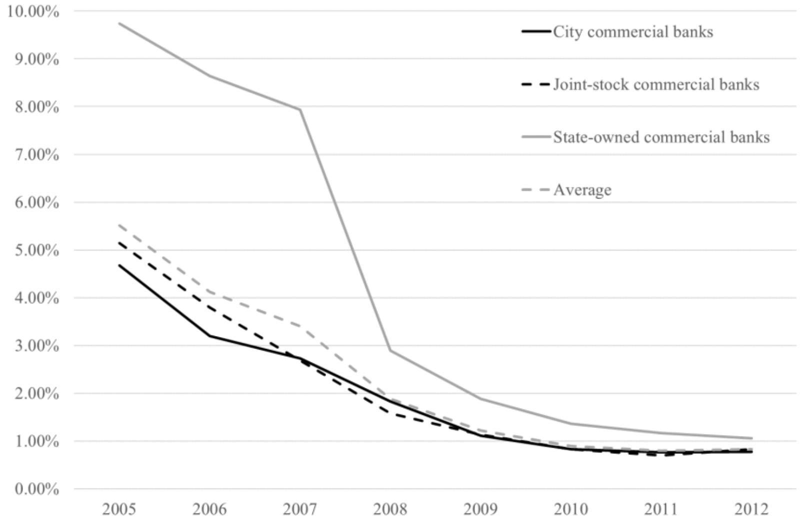
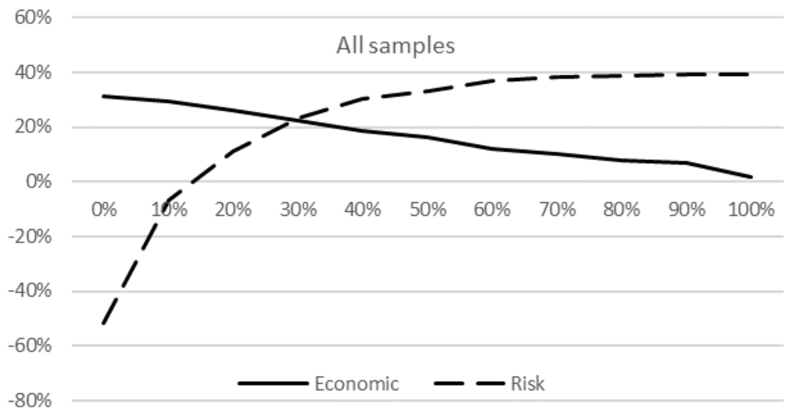
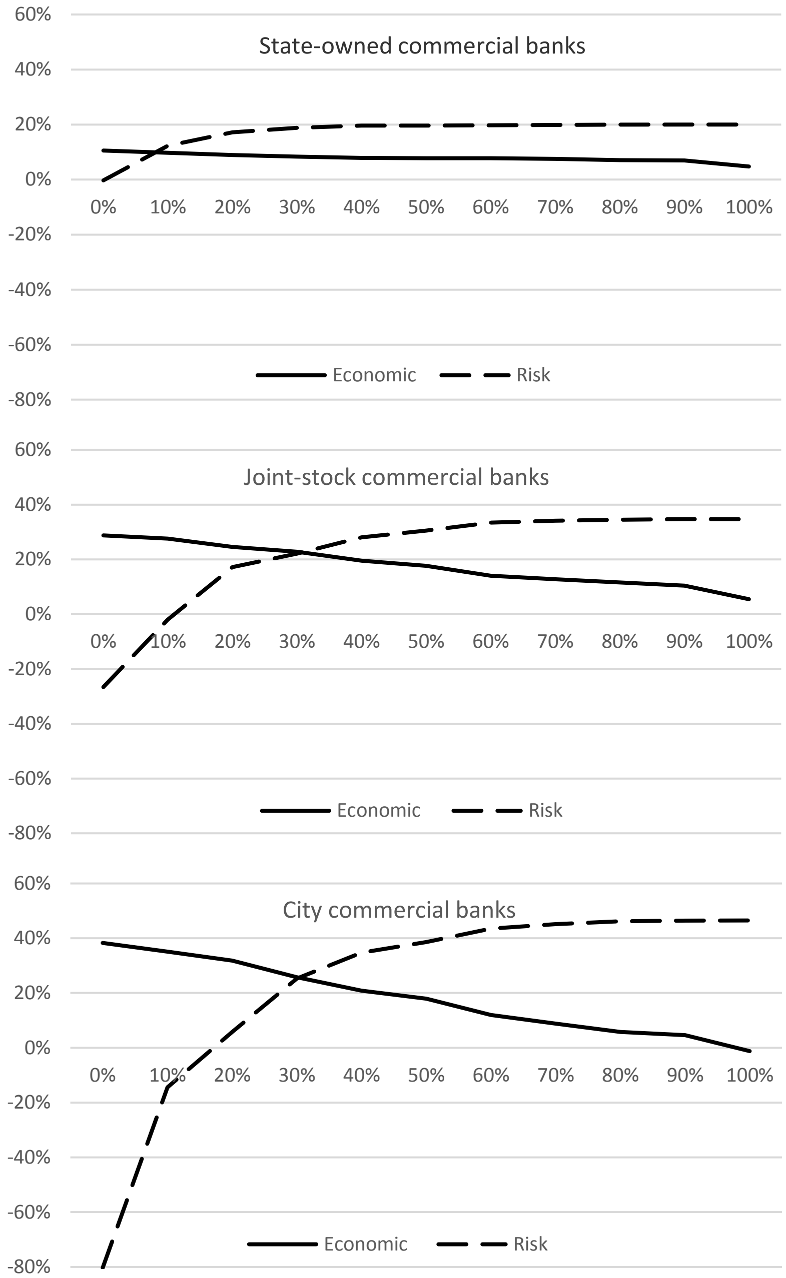


Figure 2 Tradeoff between economic and risk performances



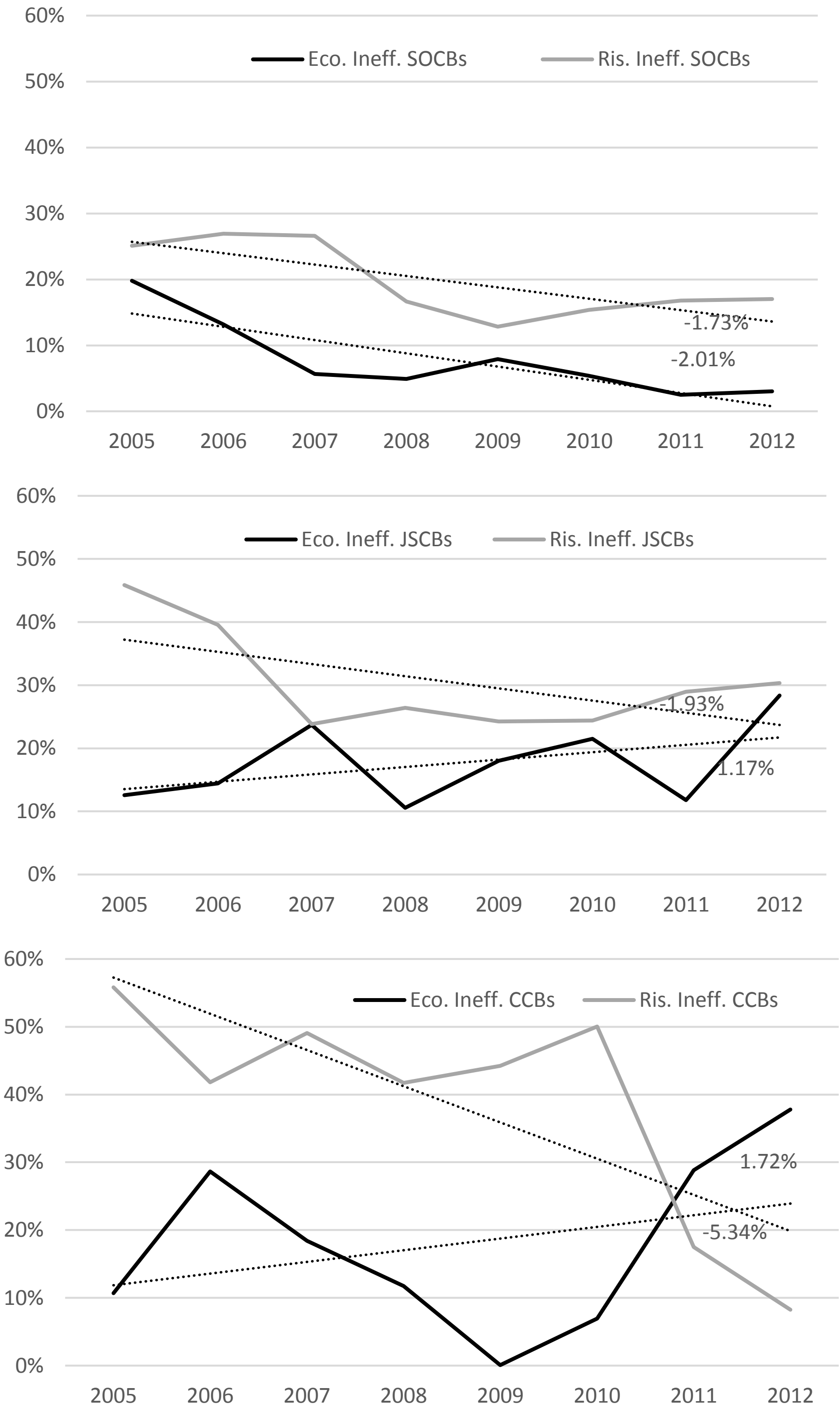
Note: Potential improvement in economic or risk performance is plotted on the vertical axis and the weight corresponding to risk control is on the horizontal axis

Figure 3 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

Figure 4 Evolution of economic and risk performance for scenario 6



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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