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Nonparametric shadow pricing of non-performing loans: A study of the Chinese banking sector

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Abstract: A number of recent studies have modeled risk in banking by incorporating undesirable outputs such as non-performing loans into the banking production technology. However, most of the banking performance studies focus on the measurement of efficiency and productivity of financial institutions without considering the impact of non-performing loans on their profits. In this paper, we introduce a novel approach for modeling a bank's technology as a multi-stage production process. We use a nonparametric estimation framework to obtain the shadow prices of non-performing loans, which approximate the potential increase in a bank's profits following a reduction in its non-performing loans. We illustrate our approach using a panel of 55 Chinese banks from 2007–2020 grouped into four categories. Our results suggest that the city commercial banks' corresponding shadow price estimates have been among the highest in the sample, whereas the policy banks have had the best risk performance among the types of institutions we considered. We also demonstrate that the substantial disparities we observe among the different types of banks have been decreasing with time.

Keywords: Data Envelopment Analysis; shadow price; undesirable outputs; dual formulation; non-performing loans.
JEL Classification: G20, G12.

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1 Introduction

Following the Asian financial crisis of 1997-1998, the global economy continued to face a multitude of risks. For example, the subprime mortgage crisis of 2008 triggered a turmoil in the global financial system and exposed a number of shortcomings of the regulatory framework used to oversight financial institutions. Among the risks posed to the global economy, studies have mentioned the credit risk associated with the pro-cyclical nature of the financial intermediation as being particularly serious (Zhang et al. 2020). The global financial crisis has caused tremendous damage to the world economy with banking sectors around the world affected to varying degrees (Jawadi et al. 2019, 2020). Consequently, ultra-loose monetary policy of near-zero interest rates and the resulting heavy borrowing by banks has been one of the main strategies the emerging economies have pursued to stimulate growth (Barnett and Sergi 2018). Consequently, the debt levels continue to increase, highlighting the importance attributed to problem assets such as the banks' non-performing loans (Hasannasab et al. 2019). Indeed, problem assets such as the non-performing loans (NPLs) have been one of the most important factors that have harmed the steady development of the banking industry.

The majority of the vast number of the existing bank performance studies have focused on the evaluation of the efficiency and productivity of the banking industry using a wide range of methods to approximate the banking technology.[1] However, many of them have neglected the issue of the risk inherent to banking, which can be modeled using the non-performing assets such as the NPLs.[2] Properly accounting for the NPLs is important when measuring the efficiency of banks, because they represent an unintended output that is undesirable from the society's perspective.

The production technology used by banks can be approximated using both parametric and non-parametric methods. Given the relative flexibility of the latter, we use the non-parametric framework to assess the impact of NPLs on the banks' revenues. Unlike previous studies, we explore bank performance using the concept of shadow

[1] See, for example, Liu et al. (2020), Galariotis et al. (2021), or Boubaker et al. (2020) for some of the most recent studies of bank efficiency. Berger and Humphrey (1997) provide an important overview of the earlier studies of the efficiency in banking.

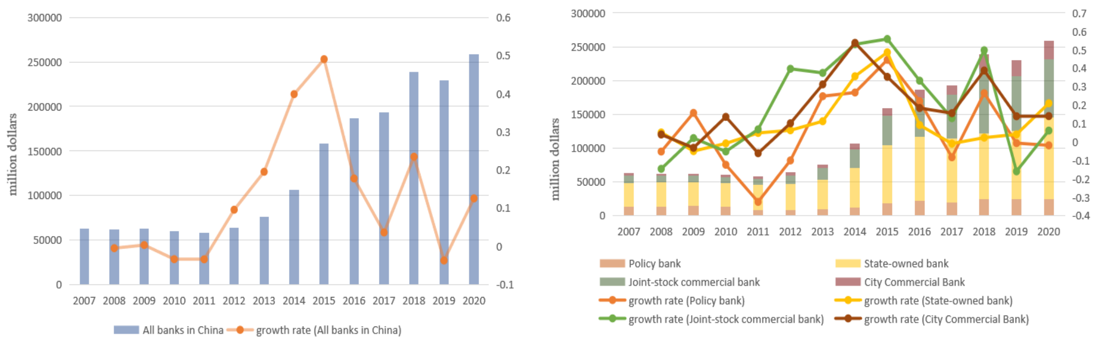
[2] Early papers using problem loans to approximate risk include Charnes et al. (1990), Berg et al. (1992), and Hugues and Mester (1993), among others. See also Guarda et al. (2013), Fujii et al. (2014), or Mamatzakis (2015) for more recent studies.

value, which can be used to measure the relative value of the inputs and outputs, whose corresponding market prices are either unobservable or difficult to measure (Leleu 2013). For example, while the market price of NPLs is not easily observable, its shadow price can provide valuable information to banks. First, if the market prices of all outputs are available, the shadow price of NPLs can be used to determine whether a bank's output structure is consistent with the goal of maximizing profits. Second, the unobservable prices can be recovered by relying on the market price of the intended output and the ratio of the intended to the unintended output. Using this logic, the shadow price of NPLs can be shown to approximate the impact of the change in the undesirable output, or the NPLs, on the intended output, or the revenue.

In this study, we make three main contributions to the existing literature. First, we attempt to fill the gaps in the bank performance literature by revisiting the relatively unexplored topic of shadow prices that can be assigned to NPLs. Compared to the takeaways from studies aimed at measuring banking inefficiency, the shadow prices of NPLs can help bank managers better understand the relationship between the intended and undesirable outputs. Second, by modeling the banking technology as a multi-stage process, we propose an improved methodology for estimating these shadow prices. We "open" the so-called "black box," typical of the standard approaches for measuring banking efficiency, by distinguishing between the different intermediate production processes, or sub-technologies, comprising our general model. Third, we rely on a relatively rich sample of banks for our empirical illustration. Unlike some of the existing studies that focus on one type of bank only, we consider a relatively wide range of institutions representing China's four important bank types, i.e. the policy banks, large state-owned commercial banks, joint-stock commercial banks, and city commercial banks, thereby making our conclusions more valuable to the policymakers.

Following the 1997-1998 financial crisis, between 30% and 40% of the loans were categorized as non-performing in China, forcing the Chinese government to actively boost lending to help the state-owned commercial banks deal with non-performing assets of more than 2.6 trillion yuan (Zhao 2021). A decade later, the 2008 global financial crisis caused the non-performing loan rate of the Chinese banking industry to rise again. More recently, with the economic conditions changing frequently both domestically and abroad, the Chinese banks found themselves in a relatively complex environment and had to face a number of new challenges (Lee et al. 2021; Zhu et al. 2019). On the one hand, the application of the big data tools and the emergence of the new data-processing technologies have had a significant impact on the traditional financial institutions by allowing them to dramatically improve their risk management processes. On the other hand, the banking industry had to face increased competition in the face of significant private capital flows into the financial market. As shown in Figure 1, the value of NPLs was relatively stable prior to 2013, but started to increase thereafter, owing primarily to the pro-cyclical nature of the banking industry. Meanwhile, slower economic growth triggered a fall in corporate profits, especially among the small and medium-sized enterprises with excess capacity and relatively weak resistance to risk, causing a decline in the quality of bank credit. After peaking in 2015, the growth of the value of NPLs began to slow down due to better monitoring of credit risk as the banks directed their efforts towards the reduction of their NPLs.

Looking at the right-hand side panel of Figure 1, we can see that the state-owned banks accounted for the largest proportion of NPLs in China between 2007 and 2020, followed by the joint-stock commercial banks, while the policy banks have experienced the highest degree of fluctuation in the growth rate of NLPs. As banks attempt to provide quick and efficient responses in the face of complex and ever changing economic conditions, the reliable estimates of shadow prices can help bank managers identify the best strategies for improving the competitiveness of their institutions.



Non-performing loans of all banks in China

Non-performing loans of different banks

Figure 1. Non-performing loans of the Bank of China (2007-2020)

The remainder of the paper is organized as follows. In the next section, we provide a brief review the related research. In Section 3, we describe the methodology we used to obtain the efficiency measures and shadow prices for inputs and outputs. We describe our dataset in Section 4 and go over the empirical results in Section 5. Finally, Section 6 concludes our study.

2 Literature review

Banking performance literature can be roughly divided into parametric and non-parametric studies. The former mainly use the stochastic frontier approach (SFA), introduced by Aigner et al. (1977) and Meeusen and van den Broek (1977) and subsequently expanded by Battese and Coelli (1988, 1992) and Khumbhakar (1990). The SFA models require imposing potentially restrictive assumptions with respect to both the parametric form of the production function used to model a bank's production process and the distribution of the error term representing its associated inefficiency level. Although the estimation results can be sensitive to these ad hoc assumptions, the efficiency rankings of observations can remain relatively unaffected (Greene 1990).

The data enveloping analysis (DEA), popularized by Charnes et al. (1978), is a non-parametric linear programming-based alternative that allows to measure efficiency in a conventional multi-input and multi-output setting. It does not require any assumptions regarding the form of the underlying technology and it has been a very popular choice for measuring the performance of commercial banks.[3] For example, Sherman and Gold (1985), who were among the first to apply DEA in banking, highlight the usefulness of the DEA methodology for evaluating bank performance but outline some of its limitations as well. Seiford and Zhu (1999) measured the performance of U.S. commercial banks by modeling a bank's technology as a two-stage production process with separate components representing its profitability and marketability. Among the plethora of banking studies using DEA, a few examples include Camanho and Dyson (2006), who separate a sample of Portuguese banks into several groups operating under different environmental conditions and measure their efficiency and productivity. Fukuyama and Weber (2010) extend the conventional DEA framework by proposing a model that accounts for the network structure of the production process and demonstrate that this can lead to an increase in the inefficiency levels compared to a conventional DEA specifications based on a single-stage framework. Curi et al. (2013) compare the DEA estimates of inefficiency across different groups of foreign banks operating in Luxembourg and explain bank performance using various macroeconomic and regulatory indicators that can affect efficiency. Curi and Lozano-Vivas (2015) evaluate and test the response of Luxembourg banks to the 2008 global financial crisis by estimating the change in banking

[3] For the review of banking studies using DEA see Paradi and Zhu (2013).

productivity and decomposing it into the change in efficiency on the one hand and the change in banking technology on the other. These and many other similar DEA studies of banking performance ignore NPLs when modeling the banking technology. More recently, Boussemart et al. (2019) used DEA to analyze the economic and risk efficiency of Chinese banks, Fukuyama et al. (2021) proposed a minimum distance DEA model to study the efficiency of the Japanese banking industry, and Tan et al. (2021) estimated the efficiency of Chinese commercial banks using a two-stage network production process.

Approaches used in the literature to account for NPLs can be divided into three categories based on the fashion in which these problem loans are incorporated into a bank's production process. The first group includes the studies that treat NPLs as a conventional production input (Rong et al. 2017). This assumption has been criticized as being inconsistent with the theoretical underpinnings of the neo-classical production model, since it implies that undesirable outputs are allowed to increase indefinitely, resulting in unbounded production possibilities sets (Färe and Grosskopf 2003, 2004; Färe et al. 2005).[4] The second category includes approaches that treat the by-products such as NPLs as outputs and impose the so-called weak disposability assumptions requiring the undesirable and conventional outputs to change proportionally at the frontier of technology for any given level of inputs.[5] Regardless of its popularity, this methodology has some limitations when applied to the banking industry. Although the weak disposability assumption is sensible in the case of the energy sector where the emission of harmful by-products such as carbon dioxide is unavoidable, banks can reduce the volume of their problem loans or eliminate them altogether by properly assessing their loan applications. The third approach considers DEA models as components of a network structure, as opposed to treating the production technology as a black box in which inputs are converted into outputs in a single stage. Färe and Grosskopf (1996, 2000) formalize a number of multi-stage specifications allowing researchers to "open" this box and model the relationship between the overall production process and its individual interdependent components, or sub-technologies, where the outputs of one of the sub-technologies can play the role of inputs in the other.[6]

[4] In their study of the Chinese banking system using network DEA, Wang et al. (2014) provide a short overview of the controversy over whether NPLs can be effectively treated as inputs and proceed to treat them as outputs along with the interest and non-interest income.

[5] See, for example, Park and Weber (2006), Fukuyama and Weber (2008), Colin Glass et al. (2010), Barros et al. (2012), Guarda et al. (2013), or Fujii et al. (2014) for some examples of this methodology.

[6] For examples of studies of performance in financial services sector using network DEA see Seiford

Network DEA has gained popularity due to its inherent flexibility allowing researchers to model the internal structure of the associated sub-technologies. Indeed, Kao (2017, 2020) suggests that, whenever possible, network-based approaches should be preferred in empirical studies. Hence, we will rely on network DEA in our application given its flexibility and popularity in modeling multi-stage production.

Despite their abundance, most of the existing banking performance studies using DEA focus on banking efficiency but do not attempt to estimate the shadow price of NPLs. On the other hand, studies that approximate shadow prices use the black box-type specifications that do not distinguish between the intermediate and final outputs (Fukuyama and Weber 2008). Hence, our first contribution to the banking performance literature using DEA is our focus on the shadow price of NPLs, which can be used to forecast the potential increase in a bank's profits and could therefore help managers take better decisions. At the same time, performance models assuming that NPLs and a bank's conventional outputs are jointly weakly disposable are based on the assumption of proportional changes in these two output types at the margin, which is relatively unrealistic in banking. Second, most of the research on bank efficiency focuses on the relatively unrealistic, single-frontier models, which ignore the intermediate production processes characteristic of a typical banking technology. However, existing studies using the more appropriate multi-process network DEA models have largely ignored NPLs. Finally, most of the previous research on the Chinese banking system has focused on a limited number of bank categories, such as the commercial or listed banks, while disregarding other types of financial institutions, i.e. the policy banks, large state-owned commercial banks, joint-stock commercial banks, or city commercial banks, which we consider in our empirical illustration.

3 Methodology

In this section, we introduce our nonparametric method for modeling the bank production technology and estimate the shadow price of NPLs assuming multiple production frontiers. We first introduce a convex, network-based banking technology and subsequently derive the corresponding dual formulation allowing us to obtain the shadow values of inputs and outputs.

---

and Zhu (1999), Kao and Hwang (2010), Matthews (2013), Fukuyama and Weber (2008, 2010, 2015, 2017) or Fukuyama and Matousek (2017, 2018).

3.1. Production technology and distance function

As discussed in Section 2, both parametric and nonparametric approaches can be used to approximate a banking technology. Among the latter, the two families of models popular in the literature include the single production frontier models and the multiple-frontier specifications. Approaches falling into the first category assume that the different output types are produced simultaneously and include the slack-based models, which treat the undesirable outputs as traditional inputs, or the weak disposability-based specifications, which treat them as outputs representing the by-products of the process whereby banks provide financial services. The second category includes the approaches that split the entire banking technology into different but interrelated sub-technologies, each corresponding to a separate production frontier. Following the recent network DEA study by Fukuyama and Tang (2022), who measure inefficiency along several dimensions including innovation, profitability, and corporate social responsibility, we propose a model of a bank's production technology based on primal and dual specifications.

We begin with a general overview of the theoretical framework required to formalize the banking technology. We use a variation of the intermediation approach to modeling production in banking (Sealy and Lindley 1977) and assume that K banks use inputs x representing the different costs of routine banking to produce final outputs y. Following Fukuyama and Tang (2022), we assume that among those inputs only the deposits, denoted by x^4, can generate the undesirable outputs, or NPLs, denoted by b. We further assume that the intermediate outputs such as the transactional financial assets and conventional loans, respectively denoted by z and w, can play the role of either inputs or outputs at the different stages of the production process.

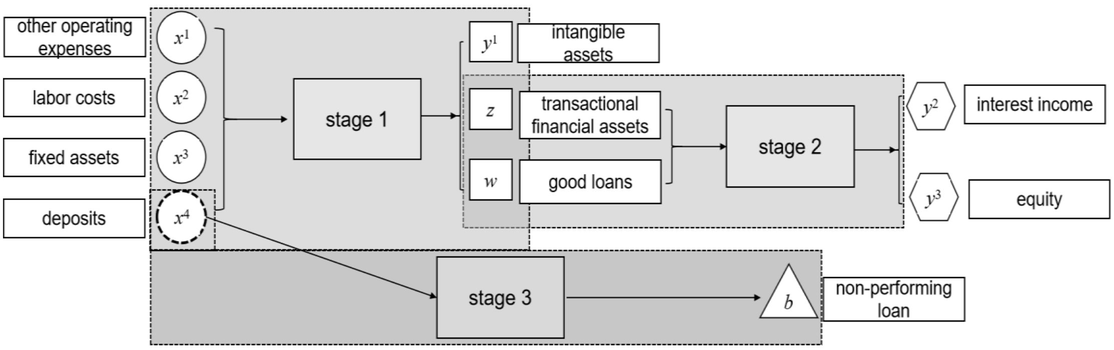


Figure 2. Model of a bank's production process.

Figure 2 illustrates the three sub-technologies comprising this multi-stage production process. At the first stage, corresponding to the first of the three types of frontiers we define, the four inputs x^1 through x^4 "produce" the intangible assets y^1, or one of the final outputs, as well as two intermediate outputs z and w. At the second stage of production, these intermediate outputs assume the role of inputs and generate two additional final outputs, i.e. the interest income (y^2) and bank equity (y^3). Finally, the third sub-technology represents the process whereby some deposits (x^4) are converted into NPLs (b). In other words, the entire banking production technology T is defined as:

$$
\begin{aligned}
T &= T_1 \cap T_2 \cap T_3 \\
&= \left\{ \begin{matrix} (x, y, b, z, w) \in R_+ : (x^1, x^2, x^3, x^4) \text{ can produce } (y^1, z, w); \\ (z, w) \text{ can produce } (y^2, y^3); x^4 \text{ can generate } b. \end{matrix} \right\} \\
T_1 &= \left\{ (x^1, x^2, x^3, x^4, y^1, z, w) \in R_+ \mid f_1(x^1, x^2, x^3, x^4, y^1, z, w) \le 0 \right\} \\
T_2 &= \left\{ (z, w, y^2, y^3) \in R_+ \mid f_2(z, w, y^2, y^3) \le 0 \right\} \\
T_3 &= \left\{ (b, x^4) \in R_+ \mid f_3(b, x^4) \le 0 \right\}
\end{aligned}
\tag{1}
$$

where the functions f_1 , f_2 , and f_3 define the three sub-frontiers and are continuously differentiable with respect to inputs and outputs. We assume that the sub-technologies satisfy the standard axioms such as convexity, closeness, free and costly disposability, and returns to scale (Murty et al. 2012).

Following Murty et al. (2012) and Fukuyama and Tang (2022), the reduced form representation of the banking production technology can be defined as follows:

$$
\begin{aligned}
T = \Bigg\{ & \sum_{k=1}^{K} \lambda_k^1 x_k^1 \le x_{k'}^1, \sum_{k=1}^{K} \lambda_k^1 x_k^2 \le x_{k'}^2, \sum_{k=1}^{K} \lambda_k^2 x_k^3 \le x_{k'}^3, \sum_{k=1}^{K} \lambda_k^2 x_k^4 \le x_{k'}^4; \\
& \sum_{k=1}^{K} \lambda_k^1 y_k^1 \ge y_{k'}^1, \sum_{k=1}^{K} \lambda_k^1 z_k \ge z_{k'}, \sum_{k=1}^{K} \lambda_k^1 w_k \ge w_{k'}; \\
& \sum_{k=1}^{K} \lambda_k^2 z_k \le z_{k'}, \sum_{k=1}^{K} \lambda_k^2 w_k \le w_{k'}, \sum_{k=1}^{K} \lambda_k^2 y_k^2 \ge y_{k'}^2, \sum_{k=1}^{K} \lambda_k^2 y_k^3 \ge y_{k'}^3; \\
& \sum_{k=1}^{K} \lambda_k^3 x_k^4 \ge x_{k'}^4, \sum_{k=1}^{K} \lambda_k^3 b_k \le b_{k'}; \\
& \sum_{k=1}^{K} \lambda_k^1 = 1, \sum_{k=1}^{K} \lambda_k^2 = 1, \sum_{k=1}^{K} \lambda_k^3 = 1; \lambda_k^1, \lambda_k^2, \lambda_k^3 \ge 0. \Bigg\}
\end{aligned}
\tag{2}
$$

where λ^1 , λ^2 , and λ^3 are the intensity variables associated with the sub-technologies T_1, T_2, and T_3, respectively, implying the underlying sub-processes are formulated independently from one another. The constraints $\sum_{k=1}^{K}\lambda_k^1=1$, $\sum_{k=1}^{K}\lambda_k^2=1$ and $\sum_{k=1}^{K}\lambda_k^3=1$ impose variable returns to scale at each stage of production.

A directional distance function (DDF), proposed by Chambers et al. (1996), can be used to measure the distance between each bank's position in the technology set T and its corresponding efficient benchmark on this set's frontier. It is given by

$$D(x,z,w,y,b;g_x,g_z,g_w,g_y,g_b)=\sup\left\{\phi\in\Re:(x,z,w,y+\phi g_y,b-\phi g_b)\in T\right\} \tag{3}$$

where ϕ, which can be interpreted as the inefficiency score, denotes the increase in the conventional, or "good," outputs y and a simultaneous decrease in the unintended output b necessary to reach the frontier of the technology in the direction given by the mapping vector **g** and $\phi=0$ signals zero inefficiency suggesting the corresponding bank is on the production frontier.

The multi-stage, multi-frontier production process and its associated performance measures described above can be modeled using the following linear programming model:

$$\begin{aligned}
&D(x,z,w,y,b;g_x,g_z,g_w,g_y,g_b)=\underset{\phi,\lambda}{Max}\frac{1}{4}\sum_{m=1}^{4}\phi^m\\
&s.t.\sum_{k=1}^{K}\lambda_k^1x_k^1\le x_{k'}^1,\sum_{k=1}^{K}\lambda_k^1x_k^2\le x_{k'}^2,\sum_{k=1}^{K}\lambda_k^2x_k^3\le x_{k'}^3,\sum_{k=1}^{K}\lambda_k^2x_k^4\le x_{k'}^4;\\
&\sum_{k=1}^{K}\lambda_k^1y_k^1\ge y_{k'}^1+\phi^1g_{y1},\sum_{k=1}^{K}\lambda_k^1z_k\ge z_{k'},\sum_{k=1}^{K}\lambda_k^1w_k\ge w_{k'};\\
&\sum_{k=1}^{K}\lambda_k^2z_k\le z_{k'},\sum_{k=1}^{K}\lambda_k^2w_k\le w_{k'},\sum_{k=1}^{K}\lambda_k^2y_k^2\ge y_{k'}^2+\phi^2g_{y2},\sum_{k=1}^{K}\lambda_k^2y_k^3\ge y_{k'}^3+\phi^3g_{y3};\\
&\sum_{k=1}^{K}\lambda_k^3x_k^4\ge x_{k'}^4,\sum_{k=1}^{K}\lambda_k^3b_k\le b_{k'}-\phi^4g_b;\\
&\sum_{k=1}^{K}\lambda_k^1=1,\sum_{k=1}^{K}\lambda_k^2=1,\sum_{k=1}^{K}\lambda_k^3=1;\lambda_k^1,\lambda_k^2,\lambda_k^3\ge0,\phi^1,\phi^2,\phi^3,\phi^4\ge0.
\end{aligned} \tag{LP1}$$

where the nonzero vector **g**= $(g_x,g_z,g_w,g_y,g_b)=(0,0,0,g_y,g_b)$ defines the direction in which the desirable and undesirable output are mapped onto the frontier of the technology and m represents the three intended final outputs and NPLs, yielding four categories of inefficiency estimates. We set the components of the directional vector to equal the actual output values in LP1, i. e. $g_y = y$ and $g_b = b$.

Then, the dual formulation of LP1 is given by

$$
\begin{aligned}
D(x,z,w,y,b;g_x,g_z,g_w,g_y,g_b) = \underset{\pi,v}{Min}(&\pi_{x1}^1 x_{k'}^1 + \pi_{x2}^1 x_{k'}^2 + \pi_{x3}^1 x_{k'}^3 + \pi_{x4}^1 x_{k'}^4 - \pi_{y1}^1 y_{k'}^1 - \pi_z^1 z_{k'} \\
&- \pi_w^1 w_{k'} - v_1 + \pi_z^2 z_{k'} + \pi_w^2 w_{k'} - \pi_{y2}^2 y_{k'}^2 - \pi_{y3}^2 y_{k'}^3 + v_2 \\
&+ \pi_b^3 b_{k'} - \pi_{x4}^3 x_{k'}^4 + v_3)
\end{aligned}
$$

$$
\begin{aligned}
&s.t. \pi_{y1}^1 y_k^1 + \pi_z^1 z_k + \pi_w^1 w_k - \pi_{x1}^1 x_k^1 - \pi_{x2}^1 x_k^2 - \pi_{x3}^1 x_k^3 - \pi_{x4}^1 x_k^4 + v_1 \le 0, k = 1,...,K; \\
&\pi_{y2}^2 y_k^2 + \pi_{y3}^2 y_k^3 - \pi_z^2 z_k - \pi_w^2 w_k - v_2 \le 0, k = 1,...,K; \\
&\pi_{x4}^3 x_k^4 - \pi_b^3 b_k - v_3 \le 0, k = 1,...,K; \\
&\pi_{y1}^1 g_{y1} \ge 0.25, \pi_{y2}^2 g_{y2} \ge 0.25, \pi_{y3}^2 g_{y3} \ge 0.25, \pi_b^3 g_b \ge 0.25; \\
&\pi_{y1}^1, \pi_{y2}^2, \pi_{y3}^2, \pi_b^3, \pi_{x1}^1, \pi_{x2}^1, \pi_{x3}^1, \pi_{x4}^1, \pi_{x4}^3, \pi_z^1, \pi_z^2, \pi_w^1, \pi_w^2 \ge 0.
\end{aligned}
\tag{LP2}
$$

where π^1, π^2, and π^3 are the input and output shadow values resulting from the activities modeled in sub-technologies T_1, T_2, and T_3, respectively. Also, π_b and π_y represent the shadow values associated with the undesirable and desirable outputs and the variables v_1, v_2, and v_3 are the VRS constraint duals corresponding to our three sub-technologies.

Following Shen et al. (2021), we restrict the inefficiency scores to be non-negative in LP1 via $\phi^m \ge 0$, m=1,…,4, implying the next-to-last set of restrictions in LP2 are inequalities, i.e.

$$
\begin{aligned}
&\pi_{y1}^1 g_{y1} \ge 0.25, \\
&\pi_{y2}^2 g_{y2} \ge 0.25, \\
&\pi_{y3}^2 g_{y3} \ge 0.25, \\
&\pi_b^3 g_b \ge 0.25.
\end{aligned}
\tag{4}
$$

3.2. Shadow pricing of NPLs

Although the shadow price has little economic meaning in and of itself, the ratios of such prices may be useful to decision makers. For instance, the ratio of any two input shadow prices such as π_{x1}^1 / π_{x2}^1 is the marginal rate of technical substitution corresponding to these inputs, the ratio of an input to a desirable output shadow price, or π_{x1}^1 / π_{y1}^1, is the partial marginal product of that input, while the ratio any two desirable output shadow prices is their marginal rate of transformation. However, the interpretation of the shadow price ratio of an undesirable to a desirable output is less straightforward. Using the example of an increase in the carbon dioxide emissions that usually accompanies economic growth, the ratio of the shadow price of CO_2 to that of GDP can be interpreted as the marginal abatement cost, i.e. the value of the output that must be forgone in order to reduce pollution by a certain amount (Boussemart et al., 2017).

The economic value of NPLs is difficult to measure because different types of banks deal with bad loans in different ways. Our multiple-frontier specification allows us to define the ratio of the shadow value of NPLs to that of the intended final output representing the banks' total revenue. Following Boussemart et al. (2017), we can formulate it using the multipliers obtained as a solution to LP2 as

$$SP_{NPL} = \frac{\pi_b^3}{\pi_{y1}^1 + \pi_{y2}^2 + \pi_{y3}^2} . \tag{5}$$

When the pattern of change in the two types of shadow values is proportional, we can estimate the increase in the banks' total revenues caused by a reduction in their problem loans. For example, reducing NPLs expands banks' lending potential and therefore helps increase their revenues at any given level of deposits. In other words, SP_{NPL} approximates the potential gain in the desirable output that can be attributed to the fall in the undesirable output.

The values of the shadow price ratios defined using (5) and their trends can offer valuable information to policy makers. NPLs have been used to approximate the risk related to lending, and the manner in which various banks manage it while attempting to maximize profits may vary across different bank categories. For instance, a decreasing trend in SP_{NPL} combined with its relatively high values implies a relatively poor but improving risk performance as well as a significant potential for an increase in intangible assets, interest income, and/or equity that can be accomplished by reducing NPLs.

4 The data

Our empirical application uses a balanced panel of 55 banks operating in China over the period 2007–2020 classified into four different categories according to their ownership structure, including three policy banks, four state-owned banks, thirteen joint-stock commercial banks, and thirty-five city commercial banks.[7] We collect our variables from the China Stock Market and Accounting Research database (CSMAR).[8]

In Tables 1 and 2, we provide the summary statistics and detailed descriptions of the input and output variables used for the empirical illustration. An examination of the data shows significant differences among the banks included in our sample, especially in terms of their value of deposits, good loans, transactional financial assets, interest income, and equity capital. Banks appear to be relatively more similar in terms of their labor costs, fixed assets, and intangible assets, while the amplitude of variation in all other operating expenses appears to be the smallest. We also note close similarities between the summary statistics describing the banks' portfolio of problem loans and the value of their fixed assets. The value of deposits and conventional loans vastly exceeds that of all other variables and suggests the Chinese banks held an average of about 216 trillion dollars' worth of deposits used to make an average of approximately 192 trillion dollars' worth of loans. Finally, an average of roughly 1.3% of all loans were categorized as non-performing in China over the fourteen-year period we consider in our study.

Table 1. Dataset descriptive statistics (millions of 2017 US dollars).

	Variables	Arithmetic average	Standard deviation	Minimum	Maximum
x^1	Other operating expenses	23.36	69.10	5.31	1089.36
x^2	Labor costs	640.29	1329.44	7.21	8281.70
x^3	Fixed assets	2376.84	5832.63	2.52	36238.38
x^4	Deposits	216460.92	474058.76	361.37	3005174.20
z	Transactional financial assets	10280.62	38005.12	7.56	525958.58
b	Non-performing loans	2462.65	5423.72	0.15	36955.64
w	Good loans	192242.49	373239.58	744.44	2329236.43
y^1	Intangible assets	270.02	728.48	0.24	4469.63
y^2	Interest income	13619.42	24714.43	0.96	144246.93
y^3	Equity	5455.80	13045.37	49.53	68562.68

7 The detailed list of banks by category is given in the appendix.

8 Shenzhen CSMAR Data Technology Co., Ltd. <https://www.gtarsc.com>.

Table 2. Detailed description of the variables.

	Variable description
Other operating expenses (x^1)	The sum of fixed asset inventory losses, net losses from the disposal of fixed assets, net losses from the disposal of intangible assets, custody costs of repossessed assets, net losses from the disposal of repossessed assets, debt restructuring losses, donation expenditures, and extraordinary losses.
Labor costs (x^2)	The sum of employee wages, benefits, social insurance premiums, housing provident funds, union funds, employee education funds, non-monetary benefits, dismissal benefits, and share payments.
Fixed assets (x^3)	Net value of the original price of fixed assets after deducting the accumulated depreciation and the provision for impairment of fixed assets. Fixed assets are the assets held by banks, temporary facilities of construction contractors, and software that is attached to the computer hardware purchased by banks that are not separately priced.
Deposits (x^4)	The sum of bank deposits.
Transactional financial assets (z)	The fair value of financial assets such as bond investment, stock investment, and fund investment held by the enterprise for trading purposes.
Non-performing loans (b)	The sum of substandard loans, doubtful loans, and loss loans.
Good loans (w)	The value of total loans excluding non-performing loans.
Intangible assets (y^1)	Net value of the original price of various intangible assets of the bank, such as the patent rights, non-patent technologies, trademark rights, copyrights, land use rights, after deducting amortization and impairment provisions.
Interest income (y^2)	Interest charged by banks in issuing various loans to external units or individuals and the discounted interest income.
Equity (y^3)	Total equity capital of the bank.

5 Results and discussion

We use our dataset to estimate the trends in the relative shadow prices of NPLs, obtained using result (5), and compare them among the different bank categories as well as various individual banks. Recall that the shadow price ratio SP_{NPL} approximates potential gains in profits attributed to a unit reduction in NPLs and that it can be interpreted as a measure of a bank's risk performance.

As illustrated in Figure 3, the estimated group-specific average shadow price ratios show an increasing trend in the immediate aftermath of the 2008 financial crisis, which had a profound impact on the entire Chinese banking industry, before starting to decline in early 2010s. Although we can observe this pattern among all banks, the joint-stock and city commercial banks have experienced a much larger decrease in their relative shadow price of problem loans compared to the other two bank categories. This appears to be a direct consequence of their already relatively poor risk performance both before and after the crisis. For example, in 2010 and 2011 the mean shadow price ratio we observe among the joint-stock and city commercial banks was more than double the estimate for the state-owned banks and as much as ten times higher compared to the policy banks. Looking at Figure 3, we can also see that the estimates corresponding to the joint-stock and city commercial banks have had generally similar trajectories over the entire period considered. At the same time, the risk performance of the state-owned banks was worse than that of policy banks, whose associated average shadow price of NPLs was the lowest among the bank categories we considered. The policy banks' relatively low estimate suggests the potential increase in their profits caused by a fall in NPLs would have been the smallest among the bank types we considered. We believe this could be due to the obligation these banks have to finance the government-mandated initiatives without considering the resulting impact on their profits.

Starting from 2015, the shadow price estimates among the state-owned banks, city commercial banks, and joint-stock banks begin to converge to roughly 100, suggesting they stood to gain an average of approximately one hundred U.S. dollars in total profits for every one thousand-dollar decrease in NPLs. By contrast, the policy banks' average estimated shortfall was much smaller at roughly 25 dollars. The mean shadow price appears to have experienced little change since this patter emerged in mid-2010s.

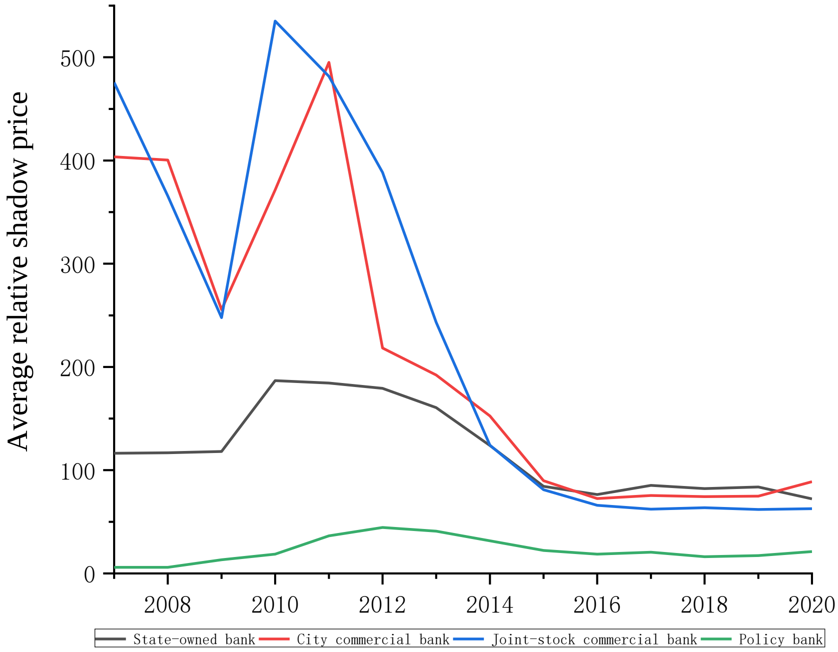


Figure 3. Average relative shadow prices of non-performing loans.

We next look at the performance of the individual banks, summarized in Figure 4. The top panels describe the results among the three policy banks and four state-owned banks, while the panels C and D illustrate the estimates corresponding to a selected group of the joint-stock and city commercial banks, respectively. Among the policy banks, we note a gradual increase in the shadow price of NPLs between 2007 and 2020, which appears to have followed a relatively steady trajectory in the case of the Export-Import Bank of China and the Agricultural Development Bank of China. On the contrary, China Development Bank's (CDB) estimated shadow price increased sharply following the 2008 financial crisis before peaking at around 110 in 2012 and subsequently converging to the levels similar to the other two policy banks. We think this fluctuation in CDB's risk performance can be explained by its emphasis on providing credit to relatively risky borrowers.

Looking next at the state-owned banks, the Bank of Communications stands out has having had both the best risk performance and the smallest change in its estimated shadow price between 2007 and 2020, while the performance of the other three state-owned banks has been rather uneven. We can also see that the Agricultural Bank of China (ABC) has had the highest shadow price estimate among all state-owned banks and therefore the most to gain from reducing its NLPs. We believe this could be one of the consequences of ABC's mission to ensure the sufficient credit flow for the rural sector as China's largest agricultural bank.

Finally, our results for the joint-stock and commercial banks vary widely, with Bohai Bank, the Postal Savings Bank of China, and the Bank of Ganzhou appearing as noteworthy outliers. The general risk performance pattern corresponding to these bank types appears to resemble the evolution in the average shadow price estimates illustrated in Figure 3. For example, the estimates appear first to increase in the immediate aftermath of the global financial crisis before converging in a generally downward trajectory.

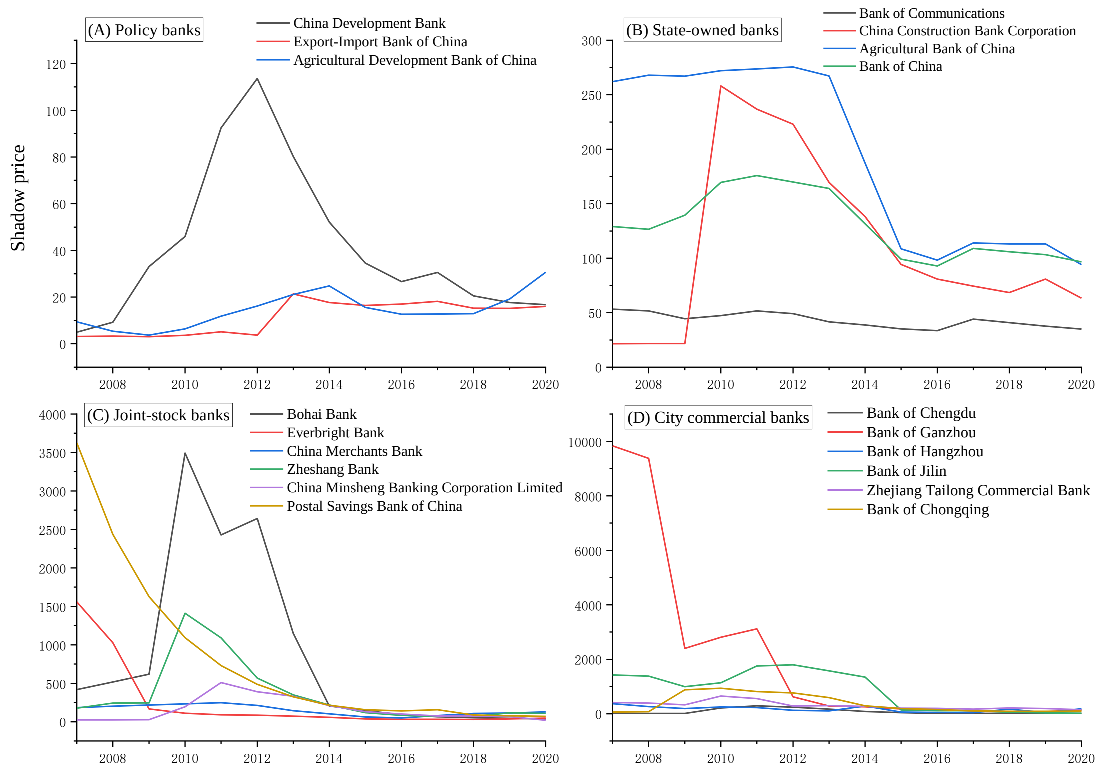


Figure 4. Shadow price of non-performing loans by bank type; selected banks.

In Figure 5, we describe bank-level estimates of the average shadow price and report the associated group-specific standard deviations. The largest dispersion in the estimates is among the city commercial banks, suggesting significant differences among the institutions included in this category. For example, our highest average shadow price estimate, or $SP_{NPL} = 2099$, corresponds to the Bank of Ganzhou that belongs to this category. The standard deviation is smaller in the case of the joint-stock commercial banks, pointing to less pronounced differences among the institutions belonging to this group compared to the city commercial banks, and the dispersions associated with the state-owned and policy banks are smaller still. For instance, the shadow price estimate fluctuates between $SP_{NPL} = 11$ (Export-Import Bank of China) and $SP_{NPL} = 43$ (China Development Bank) among the three policy banks, while in the case of the state-owned banks the results vary from SP_{NPL} = 43 (Bank of Communications) to SP_{NPL} = 194 (Agricultural Bank of China). These results are hardly surprising, considering the identities of the state-owned and policy banks as respectively the leading state investors and the providers of credit for the government-backed infrastructure projects and, therefore, the similarities among the institutions belonging to these categories dictated by the rigid roles they play.

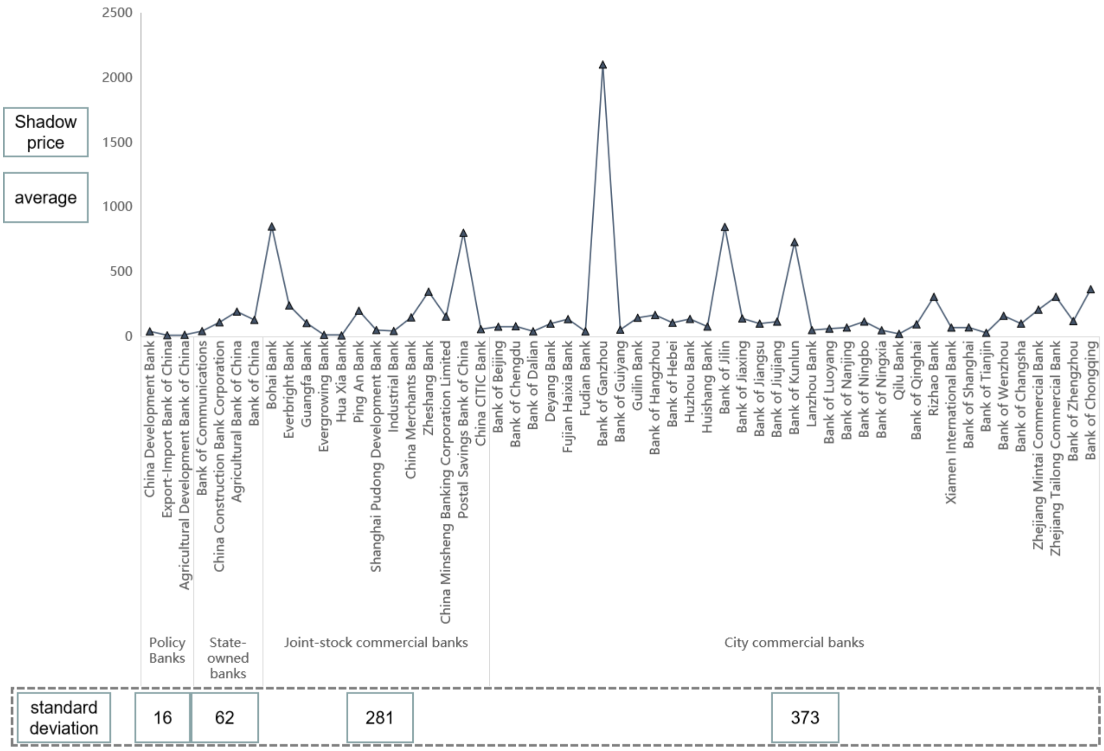


Figure 5. Bank-specific average relative shadow price; 2007 to 2020.

Finally, we assess the evolution of the disparities in the average shadow price of NPLs among our bank types using the notions of sigma- and beta-convergence. We measure sigma-convergence using the coefficient of variation of the shadow price, normalized by its group-specific mean value, and plot the results in Figure 6. With the coefficient ranging from abound 0.5 to 0.9, the disparities among the different bank types appear to be substantial but have an unmistakably downward trajectory. We also measure the convergence of the rates of change in the shadow price, or beta-convergence. Using a sample of 52 observations, we estimate the conventional growth equation assuming the shadow price growth rate is a function of its lagged value. We apply a fixed effects estimation procedure and summarize the results in Table 3. The negative and statistically significant estimate corresponding to the slope parameter of the growth model suggests absolute beta-convergence has taken place. Hence, the bank type-related disparities in both the average shadow price and its rate of change appear to be decreasing with time.

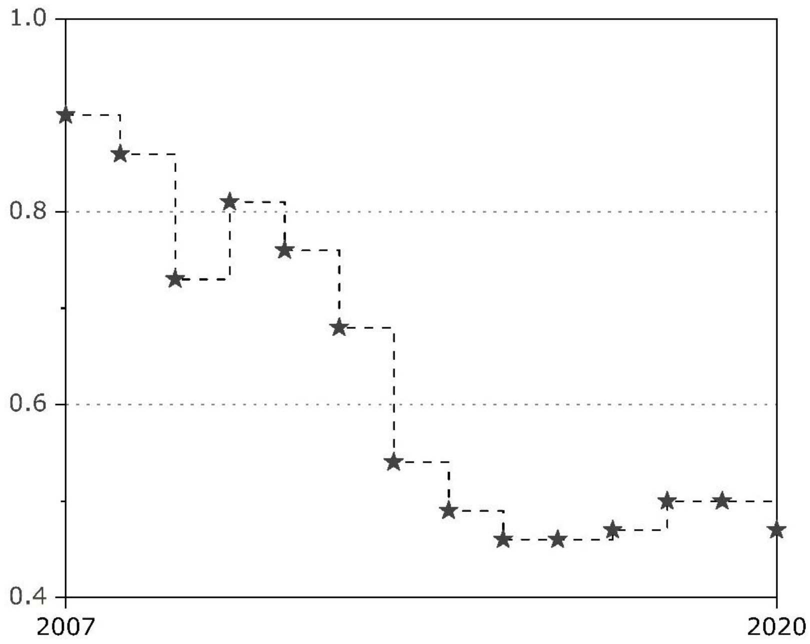


Figure 6. Coefficient of variation of SP_{NPL}; different bank types.

Table 3. Estimated absolute beta-convergence results for across the different bank types; 2007-2020.

Parameter	Estimate (standard errors in parentheses)
α	0.9878**
	(0.2267)
β	-0.2247***
	(0.0217)
R^2	0.6890

Note: ** and *** denote significance at the 5% and 1% level respectively

6 Conclusions

In this study, we estimate the shadow price of non-performing loans (NPLs) using a balanced panel of 55 Chinese banks during 2007-2020. We distinguish among four different bank categories and approximate the relative shadow price of problem loans, which can be interpreted as an increase in the profits of a bank when it reduces its NPLs. We subsequently estimate these shadow prices using a dual formulation of our network model and study their evolution by bank type, both at an aggregate and disaggregated level. We also look at the group-specific dispersion in the shadow price estimates and evaluate the change in the disparities among the institution belonging to different groups.

By focusing on the undesirable outputs such as NPLs, we tried to fill the gaps in the literature on the shadow-pricing of the by-products generated in the banking industry. Unlike the models used to study the energy sector, we do not assume that the undesirable and desirable outputs must change jointly at the frontier of the production technology – an important consideration in the case of banking. Instead, we adopt a multiple-frontier specification and model a bank's production technology as a multi-stage process. We believe our methodology can offer valuable ideas to the managers overseeing their banks' daily operations and lays a foundation for formulating important recommendations to policymakers.

Our results suggest that the policy banks have had better risk performance than any other bank type and could have increased their total profits – the sum of the value of their equity, intangible assets, and interest income – by an average of approximately \$25 for every one thousand-dollar decrease in NPLs. Conversely, the shadow price estimates characterizing the city commercial banks and the joint-stock banks are higher, implying poorer risk performance. The 2008 financial crisis, which triggered a dramatic buildup in the NPLs and had a significant negative impact on the risk performance of these bank types, appears to have caused an increase in the estimates describing the state-owned banks as well. After a period of steady decline in the immediate aftermath of the crisis, the average shadow price observed among the city commercial banks, joint-stock banks, and state-owned banks converges to roughly \$100.

In addition to the differences in shadow prices, our estimates show a varying degree of dispersion across the different bank types. The largest disparities occur among the city commercial banks, whose corresponding shadow prices range from around \$20 to more than \$2000, followed by the joint-stock banks. Nevertheless, the evolution of the coefficient of variation and the analysis of beta-convergence suggest these disparities that exist among the different types of financial institutions in China are decreasing with time.

We conclude by noting that the future work based on our proposed methodology could focus on the identification and in-depth analysis of the factors affecting the shadow price of NLPs, thereby helping policymakers pinpoint the most effective strategies for abating socially undesirable outputs in banking.

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Appendix 1. List of banks by category.

Category	Bank name
Policy banks	China Development Bank, Export-Import Bank of China, Agricultural Development Bank of China
State-owned banks	Bank of Communications, China Construction Bank Corporation, Agricultural Bank of China, Bank of China
Joint-stock commercial banks	Bohai Bank, Everbright Bank, Guangfa Bank, Evergrowing Bank, Hua Xia Bank, Ping An Bank, Shanghai Pudong Development Bank, Industrial Bank, China Merchants Bank, Zheshang Bank, China Minsheng Banking Corporation Limited, Postal Savings Bank of China, China CITIC Bank
City commercial banks	Bank of Beijing, Bank of Chengdu, Bank of Dalian, Deyang Bank, Fujian Haixia Bank, Fudian Bank, Bank of Ganzhou, Bank of Guiyang, Guilin Bank, Bank of Hangzhou, Bank of Hebei, Huzhou Bank, Huishang Bank, Bank of Jilin, Bank of Jiaxing, Bank of Jiangsu, Bank of Jiujiang, Bank of Kunlun, Lanzhou Bank, Bank of Luoyang, Bank of Nanjing, Bank of Ningbo, Bank of Ningxia, Qilu Bank, Bank of Qinghai, Rizhao Bank, Xiamen International Bank, Bank of Shanghai, Bank of Tianjin, Bank of Wenzhou, Bank of Changsha, Zhejiang Mintai Commercial Bank, Zhejiang Tailong Commercial Bank, Bank of Zhengzhou, Bank of Chongqing