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Bayesian DEA framework for market power and efficiency analysis in banking operations

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Abstract
The accurate measurement of marginal costs and market power is a persistent challenge in production economics and operations research, particularly within the banking sector. This study addresses this problem by proposing a Bayesian likelihood-based approach to estimate the Lerner index under multiple inputs and outputs, extending the nonparametric Data Envelopment Analysis methods of Fukuyama and Tan (J Oper Res Soc 73:445–453, 2022a) with statistical inference. Using data from 36 Chinese banks (2011–2018), the results reveal that market power in loans is generally higher and more stable compared to securities, with significant variations across different bank ownership types. For instance, city banks demonstrate the highest market power in loans, while state-owned banks exhibit the lowest. Efficiency analysis indicates volatility across all bank types, with no clear efficiency patterns. These findings have critical policy implications, emphasizing the need for targeted strategies to enhance market power and efficiency sustainably. For example, rural, city, and joint-stock banks should focus on staff development in non-traditional banking, while state-owned banks could benefit from operational cost reductions. The proposed methodology also provides a robust framework for future studies on market power and efficiency in diverse industries.

Keywords Data envelopment analysis · Likelihood-based approach · Marginal cost · Market power · Banking

1 Introduction

In the banking sector, industry regulators would consider increasing competitive conditions for the purpose of bank efficiency improvement. This has been evidenced by the competition-efficiency theory, which argues that banks with monopoly power will be more careless in managing expenses, which further results in a deterioration in bank efficiency (Berger and Hannan 1998). However, this is not the best scenario from an individual bank's perspective. The

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structure-conduct-performance (SCP) theory argues that a lower competitive environment induces banks to collude with each other to get higher profits (Berger 1995).

The Chinese banking industry is one of the most important sectors in the global financial system because of its size, growth path, and structural characteristics. From some perspectives, China's banking industry is the largest globally, and it plays a part and parcel role in domestic economic activities and international trade. Its banks hold considerable global financial assets, acting as major players in cross-border lending, investment, and financing initiatives, particularly under the Belt and Road Initiative of China. Moreover, the Chinese banking industry has quite a few unique characteristics that differentiate it from its global peers: state ownership of the major banks, a dual-track system combining traditional banking business with rapidly growing fintech innovation, and its rapid adaptation to regulatory reforms, including interest rate liberalization. These reforms have changed the industry from a state-controlled environment to one with increased competition, leading to a change in the dynamics of market power and efficiency. Furthermore, the high-profile challenges confronted by the industry include liquidity crises in major commercial banks and complexity associated with managing non-performing loans. These provide a fertile ground for the study of market power and its implications for risk, efficiency, and sustainability. Knowledge of these dynamics is of utmost importance for at least two reasons: one, to improve domestic financial stability, and two, to offer insights that could potentially inform policy and regulatory practices in other emerging economies.

In 2019, the Chinese government intervened in the operations of three domestic Chinese commercial banks, (namely, Baoshang Bank, Henfeng Bank, and Jinzhou Bank) because of their serious liquidity and credit crisis. Part of the reasons for the crisis is attributed to the corporate governance issue (i.e. one person or few persons has/have absolute control over the bank, while the other serious issue was the non-performing loans accumulation, which was mainly derived from three sources: (1) the bank was controlled by one or few person(s), the decision making was made by them with absolute power, and they would make loans to their friends or networks, even if the potential risk level is very high; (2) the bank was lack of risk monitoring and management mechanisms; (3) a higher level of competition in the banking industry. The first two reasons are related to the personal attributes and internal system, while the latter is mainly related to the interventions of government policy to increase competition. Therefore, in order to minimize the negative influence, market power should be enhanced, through which market share might be gained. The resulted increase in bank profitability can make the bank more selective in credit allocation, which is helpful in reduce the level of bank risk.

By the end of 2015, the interest rate liberalization had been completed in China, in other words, the government no longer had control on the upper limit of the deposit interest rate or on the lower limit of the loan interest rate. This posed a stronger competitive environment from the perspective that the individual banks would have more flexibility to manipulate the interest rate offered to depositors and businesses. How to maintain a certain level of market power has become the main concern of the bank managers.

Before providing different policy implications for market power enhancement, the first task lies in the understanding about the degree of bank market power. The empirical research has made consistent efforts during the recent decade in terms of estimating market power in both the banking sector and the non-banking industries, and much focus has been given to the indicator, which is Lerner index. The literature has been developed in this area from both empirical and theoretical perspectives, and relevant advancements in estimating Lerner index have been proposed. Traditionally, Stochastic Frontier Analysis (SFA) has been used to estimate the Lerner index based on a parametric cost function (Lopez et al. 2018; Yang et al. 2023). However, Fukuyama and Tan (2022a) proposed an alternative approach using Data Envelopment Analysis (DEA) to estimate the index via a non-parametric cost function. While traditional DEA models are valuable for measuring production efficiency—since they require no assumptions about functional forms—they are less effective in handling measurement errors (Fukuyama et al. 2024a). In contrast, SFA, though reliant on predefined functional forms, effectively separates inefficiency from random noise in data (Tan et al. 2021). Because of these differences, SFA and DEA are often seen as competing approaches. The method of Fukuyama and Tan (2022a) follows the traditional DEA approach using the nonparametric cost function. Hence, in the computation of the Lerner index Fukuyama and Tan (2022a) do not introduce stochastic terms in their cost framework.

From an economic analysis perspective, SFA has the advantage of allowing valid statistical tests (Kumbhakar et al. 2020). However, its reliance on specific distributional assumptions for inefficiency can be a limitation (Ondrich and Ruggiero 2001). To address these issues, this study develops a cost function estimation procedure that integrates the strengths of both SFA and DEA. Furthermore, Bayesian methods provide an alternative framework that overcomes some limitations of traditional SFA and DEA (Wanke et al. 2020). By incorporating prior beliefs (priors) and updating them with observed data (likelihood), Our Bayesian approach estimates the posterior distributions of the cost function and DEA-based multipliers, allowing for a more flexible, non-parametric specification of the Lerner index and enhancing the robustness of its estimation.

2 Literature review

Recent advancements in the field of banking efficiency and market power have demonstrated the importance of sophisticated econometric and operational research methods, such as stochastic and Bayesian approaches, in understanding the interplay between cost efficiency and competitive dynamics. Fukuyama et al. (2023) employed a novel dynamic network data envelopment analysis (DEA) with behavioural-causal analysis to study efficiency in Chinese banks. Their approach integrates causal constraints, allowing a more robust interpretation of efficiency scores in the context of multi-output banking operations. This methodology highlights the dual roles of production factors in the banking production process. Similarly, Badunenko et al. (2021) explored sustainable cost-efficient business models in European banks using stochastic frontier analysis. They linked long-term sustainability to the diversification of business models, emphasizing the role of cost efficiency in maintaining competitive advantage. This approach underscores the adaptability of stochastic methods to analyse both short- and long-term efficiency impacts.

The stochastic frontier approach (SFA) has been pivotal in examining cost efficiency. Galán and Tan (2024) utilized a dynamic stochastic frontier model to investigate the impact of green credit on the cost and profit efficiency of Chinese banks. Their findings reveal heterogeneous effects of green credit, with large, well-capitalized banks benefiting more significantly from such initiatives. This study exemplifies the relevance of stochastic methods in handling complex, dynamic banking data. Furthermore, Mutarindwa et al. (2021) employed true fixed effects SFA to analyse the relationship between ownership patterns and efficiency in African banks. This approach mitigates biases from unobserved heterogeneity, offering clearer insights into how bank-level characteristics influence cost and profit efficiency. Tan and Tsionas (2022) investigated sustainability efficiency in Chinese banking using panel vector autoregressive models, decomposing efficiency into internal (e.g., stability) and external (e.g., environmental and social contributions) components. This study broadens the perspective of efficiency analysis by integrating sustainability concerns, which are increasingly relevant in modern banking. The Bayesian casual analysis was also proposed by Fukuyama et al. (2024a) in validating the proposed production framework of estimating Chinese bank efficiency under the non-parametric DEA.

There has been a consistent effort in the research evaluating the level of market power. In particular, much attention has been paid by academic researchers to the evaluation of Lerner index. Elzinga and Mills (2011) discussed the origins and uses of Lerner index and critically discussed the advantages and limitations of this indicator. Besides this, comprehensive research studies used Lerner index for different purposes and this indicator has been applied to measure market power in a few economic sectors, while, as reflected from the literature, a majority of studies focused on using Lerner index for the measurement of market power in banking, although attempts have been made to estimate market power in the non-banking sectors, including the airline industry (Zhang et al. 2014); the real estate industry (Fukuyama and Tan 2023); as well as cross-industries (Correa 2012; Aghion et al. 2015).

The classification of Lerner index studies can be based on industries investigated, as illustrated above; another classification among the empirical literature can be based on the types of the research conducted. More specifically, we can divide the empirical research into two groups, with the first one focusing on the empirical perspectives of Lerner index, and the second concentrated on the theoretical perspective. Looking at the research studies related to Lerner index over the past decade, we can easily observe that the investigation of Lerner index has been conducted by the academic researchers in a comprehensive manner in the empirical context. This mainly includes, among others, the pure estimation of level of market power (competition) (Weill 2013); the examination of the relationship between market power (competition) and firm decentralization (Bloom et al. 2010); the nexus between market power and risk-taking (Bush et al. 2013; Fiordelisi and Mare 2014; Jimenez et al. 2013; Kabir and Worthington 2017; Leory and Lucotte 2017; Francis et al. 2015); the interconnection between market power (competition) and innovation (Correa 2012); the linkage between market power (competition) and cost of credit (Fungacova et al. 2017); the impact of market power (competition) on bank lending channel (Fungacova et al. 2014; Leory 2014); the relationship between market power (competition) and collateral (Hainz et al. 2013); the relationship between market power and efficiency (Ariss 2010; Koetter et al. 2012); the influence of market power on credit constraints (Love and Peria 2015); and determinants of market power (competition) (Maudos and Solis 2011; Mirzaei and Moore 2014; Zhang et al. 2014).

Instead of focusing on the investigation of Lerner index from the empirical perspective, a number of works examine the Lerner index from the theoretical perspective. Rather than using the traditional method to estimate Lerner index, which is proxied as the ratio between price marginal cost difference and price, Clerides et al. (2015) proposed a Lerner index adjusted for efficiency. Furthermore, unlike previous research using the translog cost functions for the calculation of marginal cost, the study attempted to use a flexible semi-parametric methodology. The proposed method benefits from the advantage of increasing the flexibility of the functional forms. In the estimation of Lerner index, one important component that draws much attention from the academic researchers is the marginal cost. As discussed previously, the estimation of marginal cost was undertaken using different methods, including the traditional translog cost function and the flexible semi-parametric method. Another effort to address this issue was made by Delis et al. (2014). The study differentiates itself from the previous literature by using both semi-parametric and non-parametric methods to derive the marginal cost. The method is superior compared to other traditional methods due to the fact that the requirement of imposing a specific functional form on the cost equation is released without any negative influence on the coefficient estimates of marginal cost. The results show that the values of marginal cost derived from the non-parametric method, as well as the semi-parametric method, are very close to the actual ones, and the ones derived from the traditional parametric method are significantly biased. Delis et al. (2019) also used this technique to estimate Lerner index, a component they further used to estimate bank management practice. Tsionas et al. (2018) produced another piece of unique study in the estimation of marginal cost. The output elasticity cost is used as the measurement of marginal cost. Different from the previous studies, a nonlinear system of simultaneous equations is evaluated in order to achieve this. This approach benefits from the ability to simultaneously calculate the scale elasticity and cost efficiency. Fukuyama et al. (2024b) proposed a minimum distance cost function approach to estimate the multi-output Lerner Index, linking market power with efficiency. By incorporating innovation and trade openness, their analysis demonstrates how external economic factors influence market power and cost efficiency in Chinese banks under the Bayesian causal inference analysis.

There are some studies using alternative methods to estimate market power rather than relying on the Lerner index. One of the examples is the study of Delis and Tsionas (2009), who applied the local maximum likelihood technique to jointly estimate market power and efficiency. This method possesses a number of merits and, in particular, offsets the limitation of Lerner index. More specifically, the method avoids the assumption of a global parametric functional form in the estimation of marginal cost. In addition, the local maximum likelihood method has the ability to address the issue of unobserved heterogeneity.

Bolt and Humphrey (2015) argue that the traditional Lerner index suffers from the limitation that it focused on traditional loans and deposits in the banking sector, while it does not capture the role of fee-based activities and it does not address the issue of heterogeneity in input productivity among banks. Therefore, they proposed a competition efficiency measurement, through which the cost influence, as well as the fee-based activities, are incorporated in the competition analysis. Due to the fact that the translog function suffers from the issue of misspecification, Wheelock and Wilson (2019) fill in this gap by estimating the profit and cost relationship in a non-parametric way. In addition, the moment-based corrections of Simar et al. (2017) and Hafner et al. (2018) were adopted, the framework of which allows for the inefficiency in an almost full non-parametric context. The results show that the values obtained from the proposed method are significantly different from the ones from the parametric frontier model.

Karakaplan and Kutku (2019) introduce a novel econometric method to address the issue of overparameterization by incorporating techniques from stochastic frontier analysis. This method treats market power as a supply shock, with identification relying on assumptions about the composed error term. Specifically, they posit that the conduct parameter follows a doubly truncated normal distribution.[1] Unlike traditional conduct parameter models, their approach achieves identification by exploiting the asymmetric (skewed) nature of the composed error term's distribution. This strategy allows for greater flexibility in the functional forms of demand and marginal cost functions by leveraging additional information from the error term's distribution. Furthermore, the doubly truncated normal distribution helps confine the conduct parameters within theoretical limits. They suggest estimating the parameters of the supply relationship in a single stage using a limited information maximum likelihood stochastic frontier estimation methodology, which effectively manages endogeneity.

The efficient-structure hypothesis proposed by Demsetz (1973) aruged that firms with higher levels of efficiency tend to have a level of cost, through which to gain higher levels of profits and market power. Ignoring this potential impact of firm efficiency in the estimation of firm market power could lead to biased estimates. In order to deal with this research gap, Kutlu and Sickles (2012) estimated the level of market power in the US airline industry allowing inefficiencies of the firms under a dynamic setting. The impact of efficiency on market power is also addressed by Koetter et al. (2012) in the estimation of market power through the proposal of an efficiency-adjusted Lerner index. Kumbhakar et al. (2012) proposed a stochastic frontier estimator of market power and applied it to Norwegian Sawmilling.

[1] A doubly truncated distribution is a probability distribution where values are restricted within both an upper and a lower bound. This means observations outside this range are excluded, and the probability mass is reallocated over the remaining interval to ensure the total probability sums to one. This adjustment maintains the relative likelihood of values within the specified range while excluding those outside it.

According to the duality theory of cost and input-distance functions, one can use either input price data, or input quantity data. Our new method allows for reliable estimates of market power regardless of whether constant returns to scale are assumed, unlike the new empirical industrial organisation (NEIO) approach, which does not always provide this flexibility.

Fukuyama and Tan (2022a) proposed a non-parametric data envelopment analysis (DEA) for the calculation of marginal cost and Lerner index. The proposed method was further applied to a Chinese banking dataset. While the study was the first work of its kind in the literature of data envelopment analysis in terms of its application to the measurement of marginal cost, the study suffers from the limitation that it considered the total assets as the banking outputs, while the separation between the traditional banking deposit-loan services and other businesses was not implemented.

In Summary, although there are various attempts of using Bayesian analysis and stochastic frontier analysis in estimating bank efficiency, they suffer from a number of limitations. For instance, while Fukuyama et al. (2023) incorporated behavioural-causal analysis into dynamic DEA to analyse Chinese banks, their approach does not explicitly address the statistical variability inherent in efficiency and market power estimation. Similarly, Badunenko et al. (2021) focused on the sustainability of cost-efficient business models but did not explore the implications of statistical uncertainty in marginal cost calculation or market power estimation. This study builds on these foundations by introducing a likelihood-based Bayesian framework that extends traditional DEA methods. Unlike stochastic frontier analysis (e.g., Galán and Tan 2024) or true fixed-effects models (e.g., Mutarindwa et al. 2021), our approach combines the flexibility of non-parametric methods with the rigor of statistical inference, allowing for a more precise estimation of efficiency scores and marginal costs. Furthermore, the proposed framework enables the estimation of multi-output Lerner indices while accounting for the uncertainty associated with input and output weights—an aspect overlooked in prior studies such as Fukuyama and Tan (2022a). By addressing these methodological gaps, this study not only refines the estimation of market power and efficiency but also provides new insights into the role of cost structures and competitive dynamics in the Chinese banking sector. In doing so, it offers a novel perspective that complements and extends the existing body of research, with direct implications for policy and managerial decision-making.

3 Data and methodology

The current paper uses a Chinese banking dataset covering 36 banks between 2011 and 2018. We further divide the sample into different groups based on the ownership types: they are 13 city commercial banks, 11 foreign banks, 7 joint-stock banks, 3 rural banks and 2 state-owned banks. We use three different inputs, including total deposits, personnel expenses and fixed assets. Two outputs are considered, including loans and securities following Fukuyama and Matousek (2017), and Fukuyama et al. (2020). In the proposed method, we also use relevant input prices, which are the price of funds, measured by the ratio between interest expenses and total deposits. This measurement is in line with Carvallo and Kasman (2005). The second input price is the price of capital, measured by the ratio between non-interest expenses and fixed assets, which is in accordance with Fukuyama and Tan (2022a). Finally, the price of labour is measured by the ratio between personnel expenses and total assets. **Fitchconnect database** is used for the data collection. Table 1 shows the descriptive statistics of the variables. As we can see from the table, there is a substantial variance in the level of deposits, loans, and securities, this is because the size of banks has a significant difference with state-owned banks dominating the banking industry. The differences in the prices of labour and deposits are quite small, this is because the interest rate offered on deposits is quite similar among different banks. Although it is shown in the table that there is a small variation in the price of labour, it is noticed that the highest price is 10 times of the lowest price. In the table below, we not only present the input prices but also two output prices, which are necessary in the calculation of Lerner index. We also present the coefficient of variability (CV), A CV > 1 typically indicates high variability, while a CV < 1 suggests lower variability. In this case, most variables exhibit high variability, except for 'Deposits price', 'Labour price', and 'Loans price', which show lower variability.

Table 1 Descriptive statistics

Variables	Number of observations	Mean	Standard deviation	Minimum	Maximum	Coefficien of variability (CV)
Inputs						
Total deposits	288	1,534,704.94	3,322,342. 36	2581.8	19,100,000	2.164809
Fixed assets	288	10,273.67	25,897.7	2.5	145,421	2.520784
Personnel expenses	288	7933.91	17,491.64	30.6	95,266	2.204668
Outputs						
Loans	288	924,805.95	2,151,056.66	1261.3	13,300,000	2.325955
Securities	288	446,107.39	928,746.31	181.13	5,511,866	2.08189
Input prices						
Deposits price	288	0.0249	0.0066	0.0103	0.0434	0.26506
Fixed assets price	288	5.766	11.535	0.2697	120.15	2.00052
Labour price	288	0.0057	0.0023	0.00196	0.0148	0.403509
Output prices						
Loans price	288	0.134	0.078	0.09998	0.39	0.58209
Securities price	288	0.102	0.108	0.011	1.132	1.058824

RMB million is the measurement unit of inputs and outputs. The deposits price is measured by dividing the interest expenses by total assets, the fixed assets price is measured by dividing the non-interest expenses by fixed assets, while the labour price is measured by dividing the personnel expenses by total assets. The loans price is measured by dividing the interest revenue by gross loans, while the securities price is measured by dividing the non-interest income revenue by securities

Before formally defining the Lerner index in a multi-input, multi-output setting, let us define the cost function as $C(\boldsymbol{w},\boldsymbol{y}) = \min\{\boldsymbol{w}'\boldsymbol{x}|\ \boldsymbol{y}$ is producible from $\boldsymbol{x},\boldsymbol{x} \geq 0\}$, where $\boldsymbol{x} = [x_1, \dots, x_k]' \in \mathbb{R}^K$ is a nonnegative vector of K inputs with positive prices $\boldsymbol{w} = [w_1, \dots, w_k]' \in \mathbb{R}^K$ and $\boldsymbol{y} = [y_1, \dots, y_M]' \in \mathbb{R}^M$ is a nonnegative vector of M outputs. Here is an appropriate dimensional vector of zeros. Using these notations, we define the Lerner index as

$$\frac{P_m - MC_m(\boldsymbol{w},\boldsymbol{y})}{P_m}, m = 1, \dots, M. \tag{1}$$

where P_m is the m-th output price and $MC_m(\boldsymbol{w},\boldsymbol{y})$ is marginal cost of the m-th output, i.e., $\frac{\partial C(\boldsymbol{w},\boldsymbol{y})}{\partial y_m} = MC_m(\boldsymbol{w},\boldsymbol{y})$. In our empirical illustration, two output prices are the price of loans and the price of securities. The price of loans is measured by the ratio between interest revenue and total loans, the ratio between non-interest revenue and securities is the proxy of the price of securities. We can see that the difference in the price of securities is bigger than that of the loans price, which reflects that different banks are engaged in different amounts of this business and earned different levels of revenue from it.

3.1 ***Pictorial illustration of how the Lerner index (marginal costs) and cost efficiency are estimated*:**

Before considering stochastic modeling, we first illustrate the estimation of the Lerner index and cost efficiency based on production theory in economics (Shephard 1970; 1974). We assume that production technology is described by the direct output possibility set, defined as: $P(\boldsymbol{x}) = \left\{\boldsymbol{y}\middle|\ \boldsymbol{x} \in \Re_+^N \text{ can produce } \boldsymbol{y} \in \Re_+^M\right\}$, which represents the set of all output vectors given a fixed level of inputs $\boldsymbol{x}$. The cost function is then defined as: $C(\boldsymbol{w},\boldsymbol{y}) = \min\{\boldsymbol{w}'\boldsymbol{x}|\ \boldsymbol{y} \in P(\boldsymbol{x})\}$. The indirect output possibility set is given by: $IP(\boldsymbol{w}/c) = \{\boldsymbol{y}|\ C(\boldsymbol{w}/c,\boldsymbol{y}) \leq 1\} = \{\boldsymbol{y}|\ C(\boldsymbol{w},\boldsymbol{y}) \leq c\}$, where the last equality follows from the homogeneity of the cost function of degree 1 in input prices, i.e., $C(\alpha\boldsymbol{w},\boldsymbol{y}) = \alpha C(\boldsymbol{w},\boldsymbol{y}),\ \forall\alpha > 0$. The indirect output possibility set represents the set of all output vectors that can be produced at a cost not exceeding a given total budget $c \in \mathbb{R}_{++}$.

As shown by Färe and Primont (1995), the following relationship holds: $P(\boldsymbol{x}) \subseteq IP(\boldsymbol{w}/c)$ for $(\boldsymbol{w}/c)'\boldsymbol{x} \leq 1$ and $\bigcup_{(\boldsymbol{w}/c)'\boldsymbol{x}\leq 1} P(\boldsymbol{x}) = IP(\boldsymbol{w}/c)$. Moreover, from production theory, the output possibility set can also be represented using the input requirement set: $L(\boldsymbol{y}) = \{\boldsymbol{x}|\ \boldsymbol{y} \in P(\boldsymbol{x})\}$, which implies that $\boldsymbol{y} \in P(\boldsymbol{x}) \Leftrightarrow \boldsymbol{x} \in L(\boldsymbol{y})$.

Now, consider Fig. 1a, which illustrates the input requirement set $L(\boldsymbol{y}_A)$ for Firm A. Firm A is represented by the vector $[\boldsymbol{x}_A, \boldsymbol{y}_A, c_A] = (x_{1A}, x_{2A}, y_{1A}, y_{2A}, c_A)'$, where it produces two types of outputs, (y_{1A}, y_{2A}), using two types of inputs, (x_{1A}, x_{2A}). The total cost is given by $c_A = w_1 \bullet x_{1A} + w_2 \bullet x_{2A}$, assuming the firm faces fixed input prices $\boldsymbol{w} = [w_1, w_2]'$. The point $\boldsymbol{x}^* = [x_1^*, x_2^*]'$ represents the cost-efficient input combination relative to the input requirement set $L(\boldsymbol{y}_A)$, the cost efficiency is achieved with a cost of $c^* = w_1 \bullet x_1^* + w_2 \bullet x_2^*$, which is equal to one (unity).

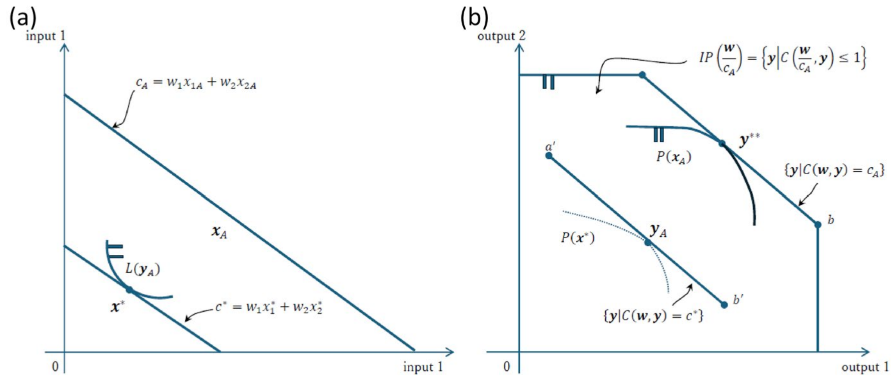


Fig. 1 **a** Input space. **b** output space

Now, turn to Fig. 1b, which illustrates the indirect output possibility set, $IP\left(\frac{w}{c_A}\right)$. The strongly cost-efficient frontier of this set is represented by the line segment a-b. From Fig. 1a, we know that $\boldsymbol{y}_A \in P(\boldsymbol{x}^*) \subset P(\boldsymbol{x}_A)$, and in Fig. 1b, $\boldsymbol{y}^{**} \in P(\boldsymbol{x}^*) \subseteq IP\left(\frac{w}{c_A}\right)$ represents a strongly cost-efficient point on the a-b line, whereas $\boldsymbol{y}_A$ does not achieve strong cost efficiency. This is because the cost efficiency score is $\frac{c_A}{c^*} < 1$, given that $\boldsymbol{y}^{**}$ satisfies $C(\boldsymbol{w}, \boldsymbol{y}^{**}) = c_A$, while $C\left(\boldsymbol{w}, \boldsymbol{y}_A\right) = c^* < c_A$.

Now, consider the cost function when fixed at c_A, i.e., $C(\boldsymbol{w}, \boldsymbol{y}) = c_A$. Taking the total derivative with respect to y_1 and y_2, we obtain: $\frac{\partial C(\boldsymbol{w},\boldsymbol{y})}{\partial y_1}dy_1 + \frac{\partial C(\boldsymbol{w},\boldsymbol{y})}{\partial y_2}dy_2 = 0$. Rearranging, this leads to: $-\frac{dy_2}{dy_1} = \frac{\frac{\partial C(\boldsymbol{w},\boldsymbol{y})}{\partial y_1}}{\frac{\partial C(\boldsymbol{w},\boldsymbol{y})}{\partial y_2}} = \frac{MC_1(\boldsymbol{w},\boldsymbol{y})}{MC_2(\boldsymbol{w},\boldsymbol{y})}$. Thus, the slope of the a-b line is given by the ratio of marginal costs at $\boldsymbol{y}^*$. By shifting this line parallelly, we obtain a new line, $a' - b'$, which passes through $\boldsymbol{y}_A$ while preserving the same marginal cost ratio as a-b.

In this study, we aim to estimate the marginal costs of an inefficient firm by leveraging information from the efficient portion of the relevant indirect output possibility set. This approach is grounded in production theory, which provides a valid basis for such an estimation.

Since multiple efficient portions may exist, we first conceptually identify the relevant one. Using this framework, we illustrate how to determine cost efficiency and marginal costs (and hence the Lerner index) for inefficient firms. Given that marginal costs should be measured relative to a frontier, we then demonstrate how to estimate the Lerner index using the multiplier DEA formulation, which will be discussed in the remainder of this section.

Following Färe et al. (1985), we consider a nonparametric (DEA) version of the cost function as:

$$
\begin{aligned}
C(\boldsymbol{w},\boldsymbol{y}) = \min_{\boldsymbol{x},\lambda}\ & \boldsymbol{w}'\boldsymbol{x}; \\
s.t. \sum_{i=1}^{n} \boldsymbol{x}_i\lambda_i &\le \boldsymbol{x}, \\
\sum_{i=1}^{n} \boldsymbol{y}_i\lambda_i &\ge \boldsymbol{y}, \\
\boldsymbol{x} \ge 0, \sum_{i=1}^{n} \lambda_i &= 1, \lambda \ge 0,
\end{aligned}
\tag{2}
$$

where $\boldsymbol{\lambda} = \left[\lambda_1, \dots, \lambda_n\right]'$ with n being the numbers of observations. The constraint $\sum_{i=1}^{n} \lambda_i = 1$ allows for variable returns to scale. We imposed $\sum_{i=1}^{n} \lambda_i = 1$, so that Eq. (2) allows for variable returns to scale. If we drop this restriction, then Eq. (2) exhibits constant returns to scale. Considering the situation where the Chinese banking industry with the bank sizes being substantial, we adopt the specification of variable returns to scale (Fukuyama and Tan 2021).

The dual to (2) is

$$
\begin{aligned}
&\max_{\boldsymbol{v},\boldsymbol{u},\omega} \boldsymbol{u}'\boldsymbol{y} + \omega\ ; \\
s.t.\quad & -\boldsymbol{v}'\boldsymbol{x}_i + \boldsymbol{u}'\boldsymbol{y}_i + \omega \le 0\ \forall i = 1, \dots, n, \\
& \boldsymbol{v} \le \boldsymbol{w}, \\
& \boldsymbol{v} \ge 0, \boldsymbol{u} \ge 0,\ \omega \in \mathbb{R},
\end{aligned}
\tag{3}
$$

where $\boldsymbol{v} = \left[v_1, \dots, v_K\right]'$ and $\boldsymbol{u} = \left[u_1, \dots, u_M\right]'$ represent the multipliers of inputs and outputs, respectively, and ω is associated with the nature of returns to scale. Considering the appendix in Fukuyama and Tan (2022a), we write the Lagrange function as

$$
\begin{aligned}
l(\boldsymbol{x}, \lambda, \boldsymbol{v}, \boldsymbol{u}, \omega) = \boldsymbol{w}'\boldsymbol{x} &- \sum_{k=1}^{K} v_k \left(x_k - \sum_{i=1}^{n} x_{ki}\lambda_i \right) \\
&- \sum_{m=1}^{M} u_m \left(\sum_{i=1}^{n} y_{mi}\lambda_i - y_m \right) \\
&- \omega \left(\sum_{i=1}^{n} \lambda_i - 1 \right).
\end{aligned}
\tag{4}
$$

From the envelope theorem, it is evident that $\frac{\partial C(\boldsymbol{w},\boldsymbol{y})}{\partial y_m} = u_m$, so marginal costs are the multipliers of the output constraints in (3).

The first constraint in (3) can be written as

$$
\boldsymbol{u}'\boldsymbol{y}_i = \alpha + \boldsymbol{v}'\boldsymbol{x}_i - s_i\ \forall i = 1, \dots, n, \tag{5}
$$

where $\alpha = -\omega$, and $s_i \ge 0$ represents a deviation (slack) variable. We define $\boldsymbol{s} = \left[s_1, \dots, s_n\right]'$.

A stochastic frontier model is a method used to estimate efficiency by separating deviations in observed performance into two parts: (1) random noise (e.g., errors due to external shocks) and (2) inefficiency (e.g., suboptimal resource use by banks). In this study, we assume that inefficiency follows a truncated normal distribution, ensuring that efficiency scores are always positive and meaningful.

This allows us to statistically infer market power and cost efficiency while accounting for random variations in banking performance. The constraints are $\boldsymbol{v} \geq 0, \boldsymbol{u} \geq 0, \boldsymbol{v} \leq \boldsymbol{w}$. We can interpret this as a stochastic frontier if we are willing to add the random noise ξ_i:

$$\boldsymbol{u}'\boldsymbol{y}_i = \alpha + \boldsymbol{v}'\boldsymbol{x}_i + \xi_i - s_i \; \forall i = 1, \ldots, n, \tag{6}$$

where, typically, $\xi_i \overset{iid}{\sim} \mathcal{N}\left(0, \sigma_\xi^2\right)$. In turn, the constraints on $\boldsymbol{v}$ and $\boldsymbol{u}$ can be interpreted as prior restrictions on the parameters.

From the point of view of a particular DMU, say $o \in \{1, \ldots, n\}$, the dual problem is:

$$\begin{gathered} \max_{\boldsymbol{v},\boldsymbol{u},\alpha} \; \boldsymbol{u}'\boldsymbol{y}_o - \alpha; \\ s.t. \; -\boldsymbol{v}'\boldsymbol{x}_i + \boldsymbol{u}'\boldsymbol{y}_i - \alpha \leq 0 \; \forall i = 1, \ldots, n, \\ \boldsymbol{v} \leq \boldsymbol{w}_o, \\ \boldsymbol{v} \geq 0, \boldsymbol{u} \geq 0, \alpha \in \mathbb{R}, \end{gathered} \tag{7}$$

with the understanding that $\boldsymbol{v}, \boldsymbol{u}, \alpha$ are specific to the DMU. Therefore, the problem becomes a statistical inference in model (6) using the constraints $\boldsymbol{v} \geq 0, \boldsymbol{u} \geq 0$, $\boldsymbol{v} \leq \boldsymbol{w}_o$. The problem in (7) is not unlike the problem of canonical correlation analysis, which is a way of inferring information from the cross-covariance matrices, while coefficients $\boldsymbol{v}, \boldsymbol{u}$ are sought to maximize the correlation between $\boldsymbol{x}_i$ and $\boldsymbol{y}_i$. However, the difference is that we have the deviation variables, and we need to specify a prior distribution for each parameter in order to formulate our model based on Bayesian statistics.

For σ_ξ, we assume the standard diffuse prior $p\left(\sigma_\xi\right) \propto \sigma_\xi^{-1}$, which is a distribution of the parameter with equal probability for each possible value. Our prior to adopt for $\boldsymbol{u}, \boldsymbol{v}$, and α is:

$$p(\alpha, \boldsymbol{u}, \boldsymbol{v}) \propto \exp\left(\boldsymbol{u}'\boldsymbol{y}_o\right) \cdot \exp(-\alpha) \cdot \mathbb{I}(\boldsymbol{u} \geq 0) \cdot \mathbb{I}\left(\boldsymbol{v} \leq \boldsymbol{w}_o\right). \tag{8}$$

where $\mathbb{I}(\boldsymbol{u} \geq 0)$ is the indicator function that equals one if $\boldsymbol{u} \geq 0$ and zero otherwise. Similarly, $\mathbb{I}\left(\boldsymbol{v} \leq \boldsymbol{w}_o\right)$ is defined.

One peculiarity is that the prior of $\boldsymbol{u}$ depends on $\boldsymbol{y}_o$ and the prior of α is $p(\alpha) \propto \exp(-\alpha)$, $(\alpha \in \mathbb{R})$, instead of the standard flat prior $p(\alpha) \propto$ const. From the objective function in (7), the posterior distribution is the product of the likelihood (from (6)) and the prior (from (8)):

$$\begin{gathered} p(\alpha, \boldsymbol{u}, \boldsymbol{v} | \boldsymbol{s}, D) \propto \exp\left(\boldsymbol{u}'\boldsymbol{y}_o - \alpha\right) \cdot \sigma_\xi^{-(n+1)} \cdot \mathbb{I}(\boldsymbol{u} \geq 0) \cdot \mathbb{I}\left(\boldsymbol{v} \leq \boldsymbol{w}_o\right) \cdot \mathbb{I}(\boldsymbol{s} \geq 0) \\ \exp\left(-\frac{1}{2\sigma_\xi^2} \sum_{i=1}^{n} \left(\boldsymbol{u}'\boldsymbol{y}_i - \alpha - \boldsymbol{v}'\boldsymbol{x}_i + s_i\right)^2\right), \end{gathered} \tag{9}$$

where D denotes the data. In (9), the first line contains prior information, and the second line contains information from the second constraint in (7). Alternatively, we can write the posterior as

$$p(\alpha,\boldsymbol{u},\boldsymbol{v},\boldsymbol{s}|D) \propto \exp\left(\boldsymbol{u}'\boldsymbol{y}_o - \alpha\right)\cdot\sigma_\xi^{-(n+1)}\cdot\mathbb{I}(\boldsymbol{u}\geq 0)\cdot\mathbb{I}\left(\boldsymbol{v}\leq\boldsymbol{w}_o\right)\cdot\mathbb{I}(\boldsymbol{s}\geq 0)\cdot \exp\left(-\tfrac{1}{2\sigma_\xi^2}\left(\boldsymbol{Yu}-\alpha\boldsymbol{\iota}_n-\boldsymbol{Xv}+\boldsymbol{s}\right)'\left(\boldsymbol{Yu}-\alpha\boldsymbol{\iota}_n-\boldsymbol{Xv}+\boldsymbol{s}\right)\right) \tag{10}$$

where $\boldsymbol{\iota}_n$ is a vector of ones in $\mathbb{R}^n$, $\boldsymbol{Y}$ is the $n\times M$ matrix containing all observations of outputs, and $\boldsymbol{X}$ is the $n\times K$ matrix containing all observations of inputs.

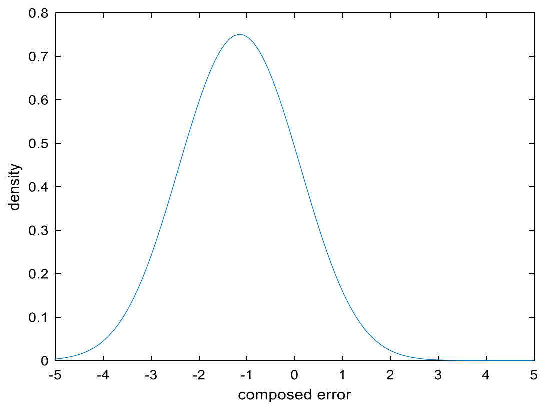
Of course, we need to integrate out the deviation variables $\boldsymbol{s}$ from the posterior in (10). To do this, it is usually assumed that the $s_i\,'s$ follow an exponential or half-normal distribution. Here, we do not follow this practice and we assume that we are agnostic about the distribution of the deviation variables. To represent knowing 'nothing' about the deviation variables, we assume

$$p(\boldsymbol{s}) \propto \text{const.}\prod_{i=1}^{n}\mathbb{I}\left(\epsilon\geq s_i\geq 0\right), \tag{11}$$

viz. we assume a flat prior in $(0,\epsilon)$ for some upper bound $\epsilon>0$. To determine the upper bound, notice that efficiency is $R_i=\exp\left(-s_i\right)$ and R_i should be between zero and one. In practice, efficiency is never zero, so a lower bound of 0.1 is quite reasonable, which in turn gives $\epsilon=2.302$. For practical purposes, this should be considered adequate. When $\sigma_v=1$, the density of the composed error is shown in Fig. 2.

Markov Chain Monte Carlo (MCMC) is a simulation-based approach used in Bayesian estimation to approximate complex posterior distributions. Since direct computation of the posterior distribution is often infeasible, MCMC iteratively generates samples from the probability distribution, gradually converging to the true posterior. In our analysis, MCMC allows us to estimate efficiency scores and Lerner indices while incorporating statistical uncertainty. This is particularly useful when dealing with complex economic models where analytical solutions are not straightforward. In turn, the posterior becomes:

Fig. 2 Density of composed error



$$p(\alpha, \boldsymbol{u}, \boldsymbol{v}, \boldsymbol{s}) \propto \exp\left(\boldsymbol{u}'\boldsymbol{y}_o - \alpha\right) \cdot \sigma_\xi^{-(n+1)} \cdot \mathbb{I}(\boldsymbol{u} \geq 0) \cdot \mathbb{I}\left(\boldsymbol{v} \leq \boldsymbol{w}_o\right) \cdot \mathbb{I}\left(\epsilon \boldsymbol{\iota}_n \geq \boldsymbol{s} \geq 0\right) \cdot \exp\left(-\frac{1}{2\sigma_\xi^2}\left(\boldsymbol{Yu} - \alpha\boldsymbol{\iota}_n - \boldsymbol{Xv} + \boldsymbol{s}\right)'\left(\boldsymbol{Yu} - \alpha\boldsymbol{\iota}_n - \boldsymbol{Xv} + \boldsymbol{s}\right)\right) \tag{12}$$

We notice that for the stochastic cost frontier model $c_i = \boldsymbol{z}_i\prime\beta + e_i - \delta_i$, c_i is observed total cost, $\boldsymbol{z}_i$ represents a $(M+K+1)$ vector of observed outputs and input prices for the i-th DMU where its first element is one, and β is a $(M+K+1)$-dimensional vector to be estimated. When $e_i \overset{iid}{\sim} \mathcal{N}\left(0, \sigma_e^2\right)$ and $p\left(\delta_i\right) \propto \mathbb{I}\left(\epsilon \geq \delta_i \geq 0\right)$, the density of the composed error $\xi_i = e_i - \delta_i$ is well-defined, and it is given by

$$p\left(\xi_i\right) = \frac{2}{\sigma_e}\left\{\Phi\left(\frac{\epsilon + r_i}{\sigma_e}\right) - \Phi\left(\frac{r_i}{\sigma_e}\right)\right\},$$

where $r_i = c_i - \boldsymbol{z}_i'\beta$.

Illustrative example:

To illustrate Bayesian estimation, suppose we would like to estimate the efficiency of a bank. If the prior belief suggests that bank efficiency follows a uniform distribution between 70 and 90%, and our observed data suggest an efficiency score of 85%, the Bayesian posterior combines these sources of information to refine our estimate. Suppose the posterior distribution centers around 83% with a 95% confidence interval of [78%, 88%], this means that after updating our beliefs with observed data, we have a high probability that the bank's true efficiency lies in this range.

Of course, a more standard and quite general assumption is that:

$$s_i \overset{iid}{\sim} \mathcal{N}_+\left(\mu, \sigma_s^2\right) \forall i = 1, \ldots, n, s_i \geq 0 \tag{13}$$

viz. $\mathcal{N}_+\left(\mu, \sigma_s^2\right)$ is a truncated normal distribution. It has been shown that the exponential and half-normal are special cases of the truncated normal distribution (Meesters 2012). The density of the truncated normal is:

$$p\left(s_i\right) = (2\pi\sigma_s^2)^{-\frac{1}{2}} \cdot \Phi(\mu/\sigma_s)^{-1} \cdot \exp\left(-1/\left(2\sigma_s^2\right)(s_i - \mu)^2\right).$$

If we reparameterize $\frac{\mu}{\sigma_s} = \mu^*$, we have $p\left(s_i\right) = (2\pi\sigma_s^2)^{-\frac{1}{2}} \cdot \Phi(\mu^*)^{-1}\exp\left(-1/\left(2\sigma_s^2\right)(s_i - \mu)^2\right)$ and the posterior becomes:

$$p(\alpha, \boldsymbol{u}, \boldsymbol{v}, \boldsymbol{s}) \propto \exp\left(\boldsymbol{u}'\boldsymbol{y}_o - \alpha\right) \cdot \sigma_\xi^{-(n+1)}\sigma_s^{-(n+1)} \cdot \mathbb{I}(\boldsymbol{u} \geq 0) \cdot \mathbb{I}\left(\boldsymbol{v} \leq \boldsymbol{w}_o\right)\mathbb{I}\left(\epsilon \boldsymbol{\iota}_n \geq \boldsymbol{s} \geq 0\right) \cdot \exp\left(-\frac{1}{2\sigma_\xi^2}\left(\boldsymbol{Yu} - \alpha\boldsymbol{\iota}_n - \boldsymbol{Xv} + \boldsymbol{s}\right) - \frac{1}{2\sigma_s^2}\left(\boldsymbol{s} - \mu^*\sigma_s\boldsymbol{\iota}_n\right)'\left(\boldsymbol{s} - \mu^*\sigma_s\boldsymbol{\iota}_n\right)\right) \cdot \Phi(\mu^*)^{-n}, \tag{14}$$

assuming the prior $p\left(\mu^*, \sigma_s\right) \propto \sigma_s^{-1}$. This is a flat prior for μ^*.

Our Bayesian hierarchical model accounts for heteroskedasticity by allowing bank-specific parameters to follow a multivariate normal distribution with an unknown mean and covariance matrix. This ensures that variance is not constant across banks, addressing potential concerns about heteroskedasticity. Furthermore, the truncated normal distribution for error terms and the MCMC-based posterior estimation naturally incorporate variance heterogeneity.

To draw statistical inference, we use the MCMC procedure because direct computation of the posterior (14) is difficult. The procedure is a Bayesian approach to efficiency analysis. It allows for incorporating prior information and dealing with uncertainty in efficiency estimates. The steps include:

Step 1: Start with the multiplier DEA cost function model (7).

Step 2: Specify the statistical distribution of each variable to be obtained stated above.

Step 3: Specify the posterior distribution (9) as the product of the likelihood (from (6)) and the prior (from (8)).

- Define the stochastic DEA model, where outputs depend on inputs and an efficiency term.
- Assume a distribution for efficiency scores (e.g., truncated normal or beta).
- Choose priors for model parameters.

Step 4: Use an MCMC Algorithm: either Gibbs Sampling or Metropolis–Hastings Algorithm:

Step 5: Generate Posterior Samples

Step 6: Estimate Efficiency Scores and the Lerner index as estimated by Eq. (1).

Following these steps, we obtain the estimates by computing the mean of the posterior samples to estimate efficiency scores. Additionally, we calculate credible intervals (the Bayesian equivalent of confidence intervals) for the efficiency estimates and the Lerner index.

The Bayesian likelihood approach has several limitations and challenges, despite its wide applicability and theoretical appeal. The Bayesian likelihood approach relies on subjective prior selection, which can introduce bias and heavily influence the results, especially with limited data. It also often demands computationally intensive methods, such as Markov Chain Monte Carlo, which can be challenging for high-dimensional or complex models. Additionally, the approach is sensitive to model misspecification because if the likelihood function does not accurately represent the data generating process, the inferences may be misleading. Lastly, balancing the information from the prior with that from the data can be delicate, and conflicts between them may complicate interpretation. See for example Gelman et al. (2013) and McElreath (2020) for these limitations. Despite these limitations, Bayesian likelihood methods are a powerful tool when applied with care, especially when prior information is available and computational resources are sufficient. Addressing these challenges often involves thoughtful model design, sensitivity analysis, and validation against real-world data.

4 Empirical results and discussion

Marginal posterior density of the $\boldsymbol{u}$ is reported in panels (a) of Fig. 3. In panel (b), we report the sample density of posterior mean estimates of efficiency. From panel (b), efficiency averages at 83%, with a standard deviation of 0.045. The efficiency scores range from 69 to 89%.

So far, we have assumed that parameters $\boldsymbol{u}, \boldsymbol{v}$ are common to all banks. Clearly, this assumption is not reasonable, and we assume instead a multivariate normal distribution with unknown mean $\overline{\boldsymbol{\theta}}$ and covariance matrix $\boldsymbol{\Sigma}$.

Our prior for the new parameters is:

$$\left[\alpha_o, \boldsymbol{u}_o', \boldsymbol{v}_o'\right]' \equiv \boldsymbol{\theta}_o \sim \mathcal{N}\left(\overline{\boldsymbol{\theta}}, \boldsymbol{\Sigma}\right). \tag{15}$$

where o represents the bank under assessment. Also

$$p\left(\overline{\boldsymbol{\theta}}, \Sigma\right) \propto |\boldsymbol{\Sigma}|^{-\frac{K+M+1}{2}}, \tag{16}$$

which is a standard flat prior. In turn, the posterior becomes

$$p\left(\boldsymbol{\alpha}, \boldsymbol{u}, \boldsymbol{v}, \boldsymbol{s}, \sigma_\xi, \sigma_s | \boldsymbol{X}, \boldsymbol{Y}\right) \propto \tag{17}$$

$$\prod_{o=1}^{n}\left\{\sigma_{\xi,o}^{-(n+1)}\sigma_{s,o}^{-(n+1)}\right\}\prod_{o=1}^{n}\{\exp\left(\boldsymbol{u}_o'\boldsymbol{y}_o - \alpha_o\right) \cdot \mathbb{I}\left(\boldsymbol{u}_o \geq 0\right) \cdot \mathbb{I}\left(\boldsymbol{v}_o \leq \boldsymbol{w}_o\right) \cdot \mathbb{I}\left(\epsilon\boldsymbol{\iota}_n \geq \boldsymbol{s}_o \geq 0\right)\cdot$$

$$\exp\left(-\frac{1}{2\sigma_{\xi,o}^2}\left(\boldsymbol{Y}\boldsymbol{u}_o - \alpha_o\boldsymbol{\iota}_n - \boldsymbol{X}\boldsymbol{v}_o + \boldsymbol{s}_o\right) - \frac{1}{2\sigma_{s,o}^2}\left(\boldsymbol{s}_o - \mu^*\sigma_{s,o}\boldsymbol{\iota}_n\right)'\left(\boldsymbol{s}_o - \mu^*\sigma_s\boldsymbol{\iota}_n\right)\right) \cdot \Phi(\mu_o^*)^{-n}$$

$$\prod_{o=1}^{n}\left\{\exp\left(-\frac{1}{2}\left(\boldsymbol{\theta}_o - \overline{\boldsymbol{\theta}}\right)\Sigma^{-1}\left(\boldsymbol{\theta}_o - \overline{\boldsymbol{\theta}}\right)\right)\right\} \cdot p\left(\overline{\boldsymbol{\theta}}, \boldsymbol{\Sigma}\right)$$

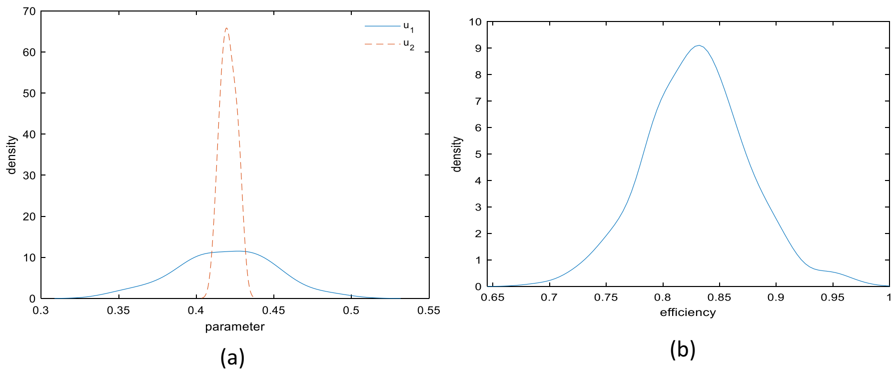


Fig. 3 Marginal posterior densities

where $\boldsymbol{u}_o, \boldsymbol{v}_o$ denote bank-specific parameters. As a result, parameters $\sigma_{\xi,o}$, $\sigma_{s,o}$, and μ_o^* are now bank-specific. Moreover, $\boldsymbol{\alpha} = \left(\alpha_1, \ldots, \alpha_n\right)'$, $\boldsymbol{u}_o = \left(u_{1,o}, \ldots, u_{M,o}\right)'$, $\boldsymbol{v}_o = \left(v_{1,o}, \ldots, v_{K,o}\right)'$, $\boldsymbol{s}_o = \left(s_{1,o}, \ldots, s_{n,o}\right)'$.

Given $\overline{\boldsymbol{\theta}}$, MCMC (Markov Chain Monte Carlo) can be implemented in parallel for each bank to obtain the bank-specific MCMC samples $\left\{\theta_o^{(j)}, j = 1, \ldots, J\right\}$, including $\left\{\sigma_{\xi,o}^{(j)}, \sigma_{s,o}^{(j)}, \mu_o^{(\delta_i),*}, j = 1, \ldots, J\right\}$. In turn, we can obtain the MCMC samples for $\overline{\boldsymbol{\theta}}$ and $\boldsymbol{\Sigma}$ using standard methods. In Fig. 3a, b, we report the sample histograms of posterior means of bank-specific $\boldsymbol{u}_o = \left(u_{1,o}, u_{2,o}\right)'$. Figure 3c reports the sample density of posterior mean estimates of efficiency. Since there are two bumps (i.e., the Kernel distribution of efficiency based on the posterior means is bi-modal), the result might suggest that the data may be stemming from two different sources. This seems in turn to suggest that u_1 and u_2 come from different distributions, indicating that the loans and the securities markets are distinct. As shown in Fig. 4, the

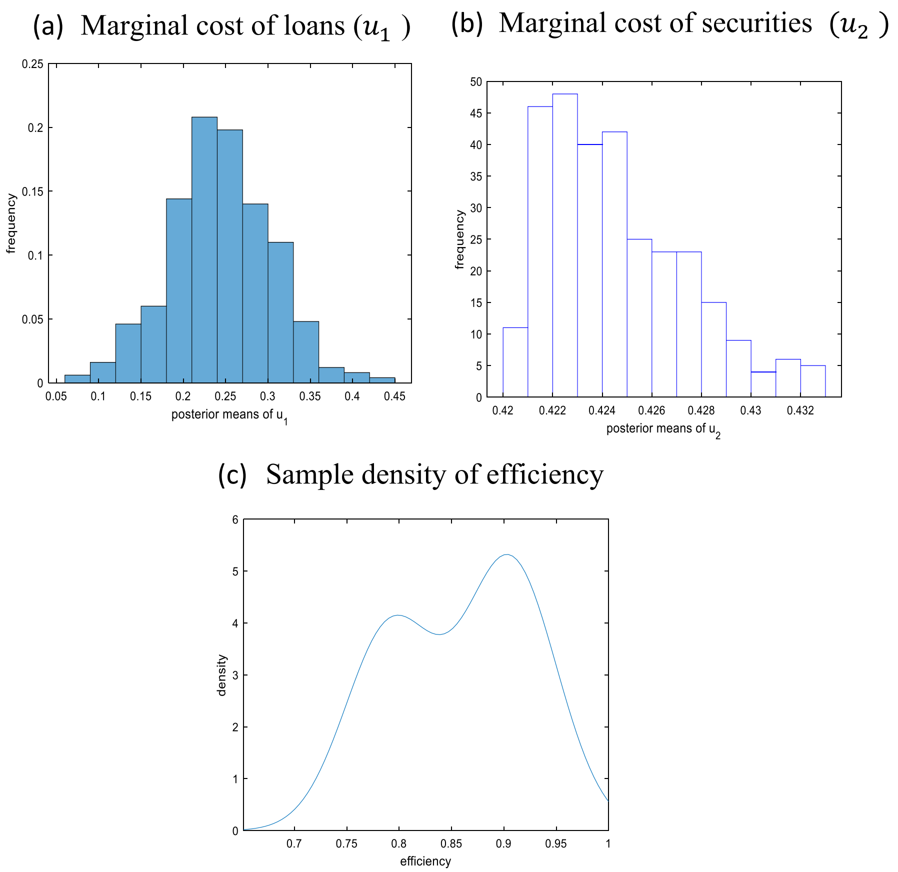


Fig. 4 Sample distributions of posterior means of bank-specific marginal costs

posterior distributions of bank-specific marginal costs exhibit variation across banks, which suggests that heteroskedasticity is present. This is naturally captured in our Bayesian framework, as the model estimates different posterior variances for each bank, confirming that a constant variance assumption is not imposed.

Figure 5a presents the (posterior mean estimated) Lerner indices for all the inputs and outputs used in the study between 2011 and 2018 for the whole sample. The figure shows that the one of the outputs, loans, has a stronger market power than that of securities. The stable market power, as reflected by the values of Lerner indices, suggests that the competition level in the loan business among Chinese banks is not high. This is because different bank types mainly served different types of enterprises or focused on a specific economic sector (i.e. state-owned banks mainly focused on large state-owned enterprises; joint-stock commercial banks mainly provided services to middle-sized enterprises, city banks focused on city-level small

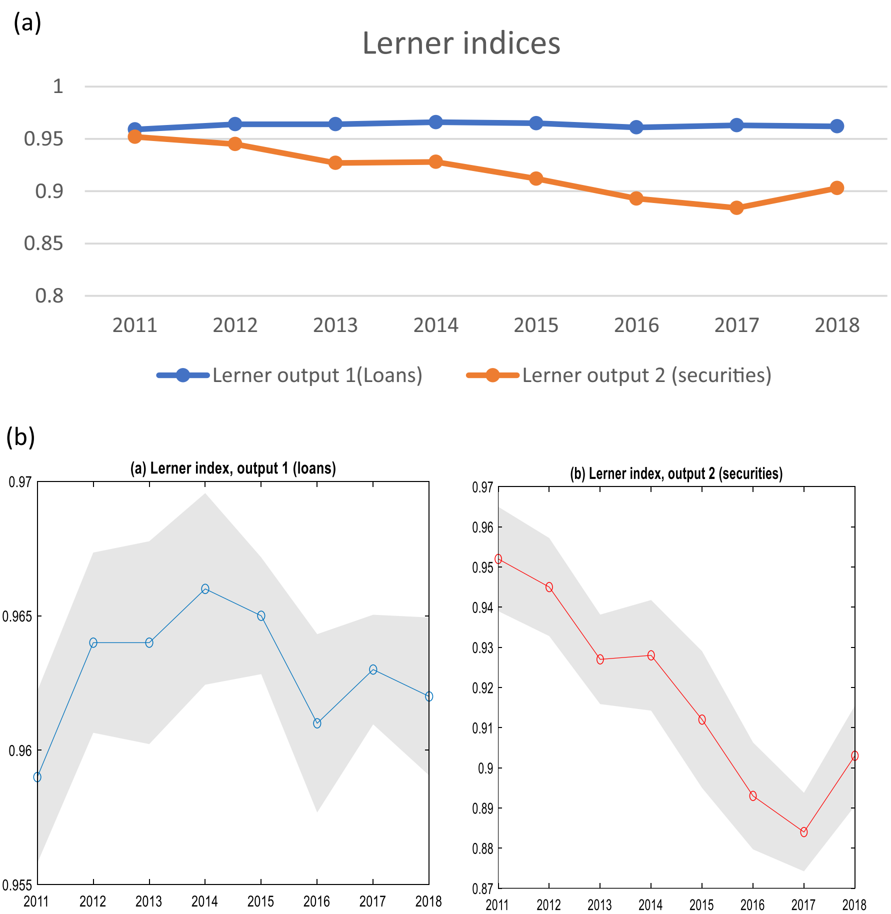


Fig. 5 **a** Lerner indices in the Chinese banking industry 2011–2018. **b** Results from Bayesian approach, Lerner indices in the Chinese banking industry 2011–2018

and private enterprises, while rural commercial banks are the main financial institutions providing loan services to agricultural related businesses and farmers in the rural area, foreign banks were mainly responsible for providing loans to foreign-owned enterprises). In Fig. 5b, we report the same Lerner indices, including the intervals of statistical uncertainty (more specifically, 95% Bayes probability intervals). Through the comparison between these two figures, we notice that both of them show a similar trend in the evolution of Lerner indices across the years. The main difference is the Bayesian estimated Lerner indices show a much clearer variation over the period. Therefore, we argue that incorporating statistical uncertainty in estimating Lerner indices under the Bayesian approach would generate more accurate and precise results.

The second output, securities, has a lower market power compared to that of loans. This is because, unlike the traditional deposits and loans businesses, the volume/size of securities businesses conducted by the banks is much smaller, so the effect of economies of scale and scope is significantly smaller than that of the traditional deposit-loan businesses, the significantly higher levels of cost, and, in particular, an increase in the marginal cost of conducting the securities businesses leads to a lower level of market power.

We further look at the marker power, as reflected by the Lerner indices for different types of bank ownership. Figure 6 shows that for all the bank types except foreign banks, the level of market power in loans is higher than that of securities in general. This coincides with Fig. 5, where we reported the level of market power in loans and securities for the whole sample. Although the four bank types (state-owned, joint-stock, city and rural banks) followed a similar trend as the one of the overall sample, a higher volatility in loans is observed for city banks, joint-stock and rural banks compared to the overall sample. In terms of foreign banks, we observe that the levels of market power in loans and securities experience a relatively higher level of volatility, with the latter being even more volatile than the former, and the results do not show a clear comparison between the level of market power in loans and the one in securities.

Finally, we look at and compare the market power of different outputs and inputs across different bank ownership types. Starting from the market power in loans, as reflected by Fig. 7a, it can be seen that the highest market power is possessed by city banks, while state-owned commercial banks have the lowest market power. For other ownership types, we notice that the market power is the highest over the early period of the examined period (2011–2015) for joint-stock commercial banks, while there is a common characteristic that they experience a level of volatility. The state-owned banks' lowest market power is mainly attributed to the higher marginal cost. In other words, increasing an additional unit of loans incurs a larger volume of additional costs. This is because state-owned banks mainly provided the loan services to big state-owned enterprises, so the volumes of loans would be significantly larger than the ones made by other bank ownership types. A large amount of additional costs incurred is mainly derived from the expenses in the process of 'network lending', during which the banking staff use various banking resources to attract loans from their established relationship or they will spend money on establishing relevant relationships. In addition, the banks also devote certain amount of resources

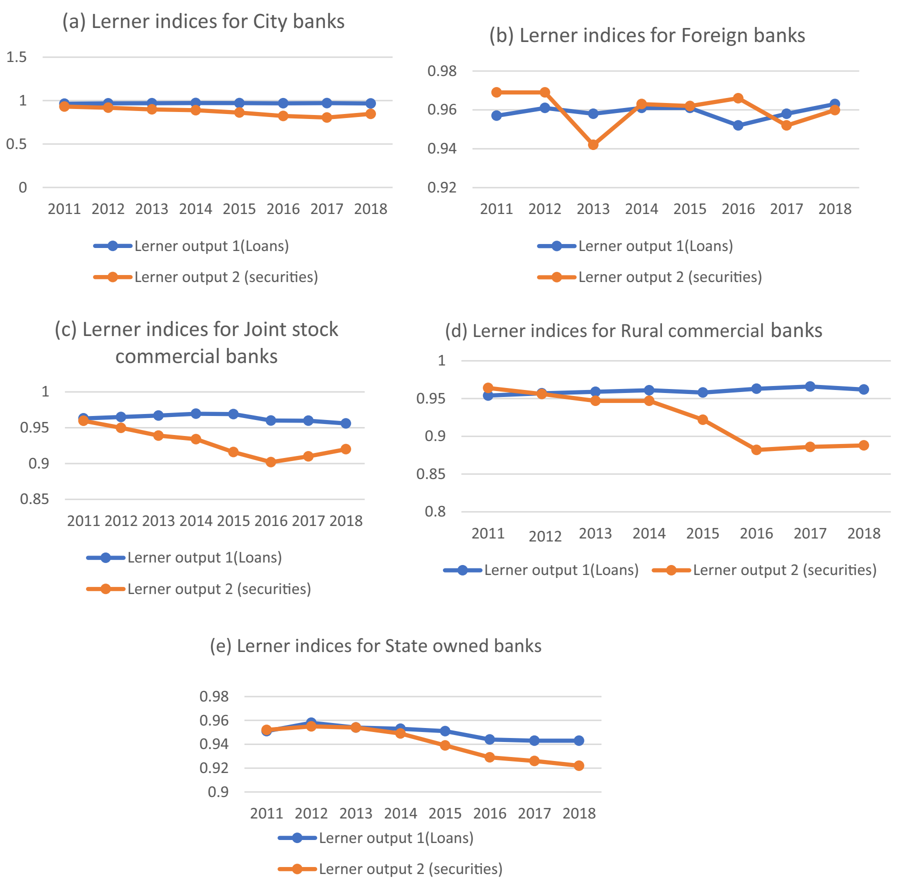


Fig. 6 Lerner indices for different ownership types

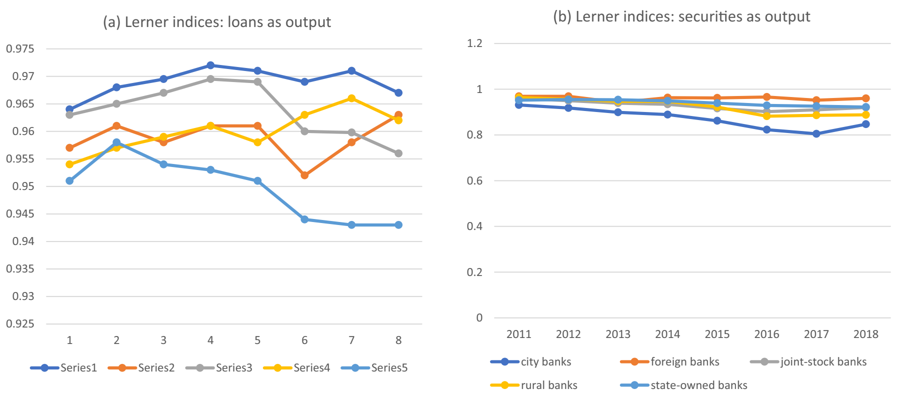


Fig. 7 Comparison of Lerner indices across different ownership types

to monitor and manage the risk of loans. For other ownership types, there would be two priorities, one of which is to reduce the level of marginal cost of loans in order to increase market power, and the other is to reduce the level of marginal cost in a consistent and sustainable way. In other words, these three ownership types should focus on increasing market power and reducing the volatility of market power.

Turning to the comparison of market power in securities among these different bank types, as reflected by Fig. 7b, the lower market power is possessed by city banks. For all the other four bank types, the level of market power was very similar from the start of the examined period up to 2015. There is a much clearer comparison among these four ownerships from 2016 to the end of the period, during which the highest market power is possessed by foreign banks. The domestic Chinese banks as a whole have lower market power in comparison to foreign banks. This is because the non-traditional banking businesses have been increasing their importance in the business portfolio, compared to foreign banks, the domestic banks are lack of skills and experience in engaging in this specific type of business and the size of the securities business conducted was much smaller. Therefore, the domestic banks should focus more on recruiting staff with higher ability and more experience in the non-traditional banking businesses. Furthermore, it was a fact that the traditional Chinese people are very conservative and the majority of them will prefer to deposit with the bank rather than opting for the non-traditional banking products (i.e. securities investment product) due to the consideration that the risk level of bank deposits would be the lowest. This results in a reduction in the level of demand and also a decrease in the price level of the non-traditional banking businesses, which partly explains the lower market power for this bank business. From the competition perspective, lower levels of demand indicate that, for this specific type of banking business, there was a customer market rather than the bank market. Customers will choose which banks they will go for, and the banks will compete more strongly to attract the customers. We used 85% Bayesian probability intervals to see whether there is a significant difference in market power among different bank types. The findings show that the difference in the market power in loans is significant, but the one in securities is insignificant.

We have briefly presented the condition of competition derived from our innovative method. Now we are going to have a closer look at bank efficiency, as well as the efficiency scores for different bank types. Figure 8 shows that the efficiency experiences a level of volatility. The figure further shows that the level of efficiency declined in 2012 compared to the start of the period, before experiencing a jump in 2013. After this, the efficiency level declined slightly in the next two years, before experiencing a strong decline in 2016. The level of efficiency increased slightly in 2017, before ending up with a substantial increase in 2018. Our results are in accordance with Fukuyama and Tan (2022b).

Figure 9 shows that there is no clear comparison among different ownership types. Overall, the highest level of efficiency was achieved by rural commercial banks in 2015, the value of which was 0.881, while the lowest level of efficiency was also obtained by the rural commercial banks with an efficiency score of 0.671. From this observation, we argue that there is still room for the Chinese commercial banks to improve efficiency through reconsidering the input

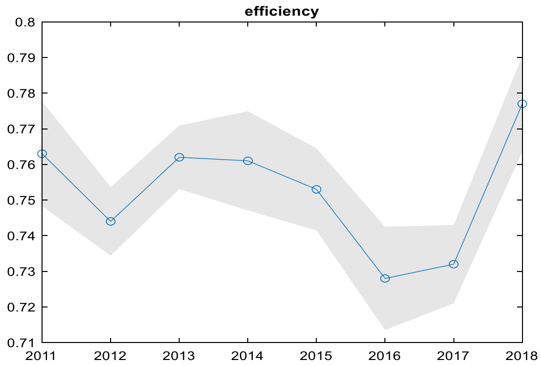


Fig. 8 Efficiency in the Chinese banking industry: 2011–2018

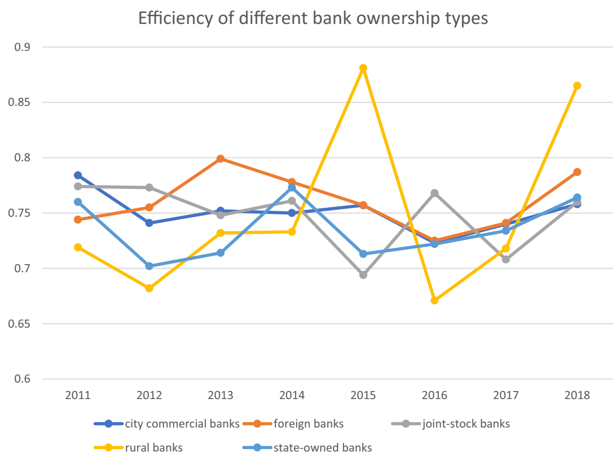


Fig. 9 Efficiency of different bank ownership in China: 2011–2018

and output allocation, while there is a characteristic noticed in the figure that all the bank types experienced a level of volatility in efficiency. Therefore, the emphasis is to improve the operation through reducing the costs in a constant and sustainable manner. Our results are in contrast with other Chinese bank efficiency studies (Dong et al. 2016; Boussemart et al. 2019). The different results are mainly attributed to the banking sample and the period investigated, as well as the method adopted to measure efficiency.

The findings of this study provide actionable insights that extend beyond academic interest, offering concrete recommendations for banking regulation and policy. One key takeaway is the high market power in loans, particularly for city banks, which underscores the need for regulators to strike a balance between fostering competition and ensuring market stability. Excessive market concentration could lead to inefficiencies, while overly fragmented competition might weaken the banking sector's resilience. Regulatory interventions could include incentives for diversification and operational reforms to mitigate risks associated with high market power.

For state-owned banks, the observed lower market power and higher marginal costs highlight the necessity of operational restructuring. Reducing dependency on government subsidies and simplifying governance structures can help these banks become more efficient and competitive. Additionally, policies that promote collaboration between state-owned and private or foreign banks could facilitate knowledge sharing and the adoption of best practices. The study also emphasizes the potential of foreign banks as benchmarks for innovation and specialization, especially in securities markets. Regulators might consider creating platforms for domestic banks to access expertise from their foreign counterparts, fostering skill development in non-traditional banking sectors. This approach could help domestic banks enhance their competitiveness in securities and other emerging areas.

Volatility in efficiency levels across all bank types suggests a pressing need for policies focused on long-term sustainability. Policymakers could encourage banks to adopt advanced risk management practices, invest in technology, and standardize efficiency measurement frameworks. Promoting ESG (environmental, social, and governance) criteria as part of regulatory assessments could also align the banking sector with global trends, ensuring both financial stability and broader societal benefits. Finally, the findings point to broader implications for financial literacy and customer engagement. Domestic banks should not only improve their marketing strategies for securities but also collaborate with policymakers to enhance financial literacy initiatives, reducing customer risk aversion. These efforts would support greater diversification in financial product adoption, contributing to a more balanced and dynamic banking ecosystem. By integrating these real-world applications into the findings, this study bridges the gap between research and practice, offering a roadmap for both regulators and practitioners in navigating the complex dynamics of market power and efficiency in the banking sector.

While this study focuses on the Chinese banking sector, its findings and methodological contributions have broader implications for banking systems and regulatory frameworks worldwide. The proposed Bayesian likelihood-based approach to estimate marginal costs and market power can be adapted to other industries and regions where multi-input, multi-output production systems prevail. For example, the method could be applied to assess market power in sectors such as telecommunications, healthcare, or transportation, where competitive dynamics and efficiency are similarly complex. The observed disparities in market power and efficiency across different types of banks offer insights into the challenges faced by economies transitioning from centralized to liberalized financial systems. Many emerging markets, such as those in Southeast Asia, Latin America, and Africa, share similarities with China in terms of undergoing rapid economic development, regulatory shifts, and financial sector reforms. Policymakers and bank managers in these regions can learn from the implications of our findings, particularly regarding the balance between competition and market power, as well as strategies to enhance efficiency while maintaining financial stability.

Additionally, the study's insights on foreign banks' success in securities markets highlight the importance of cross-border knowledge sharing and the role of global financial institutions in enhancing local market development. This finding is relevant for countries aiming to attract foreign direct investment in their financial sectors or improve their domestic banks' competitiveness by fostering collaboration with international counterparts. The volatility in efficiency levels observed across Chinese banks also resonates with the challenges faced by banks in developed markets, especially in periods of economic uncertainty or regulatory change. The emphasis on long-term sustainability, risk management, and technological innovation is equally pertinent to banking systems in advanced economies such as the EU and the US, which are grappling with issues like digital transformation, ESG compliance, and increased competition from fintech firms. By demonstrating the applicability of its methodological framework and findings across diverse financial systems, this study contributes to a deeper understanding of global banking dynamics. Future research could extend this approach to comparative studies across countries, exploring how varying institutional, cultural, and regulatory environments influence market power and efficiency. Such investigations would further validate the versatility of the proposed methods and enhance their practical relevance for global financial policymaking.

5 Robustness check

In order to examine the robustness of our results, we re-estimate the marginal cost through a translog cost function under the parametric stochastic frontier analysis, the specification is expressed as below:

$$\ln C = \alpha_0 + \sum_n \alpha_n \ln w_n + \beta \ln y + \frac{1}{2}\sum_n \sum_{n'} \gamma_{nn'} \ln w_n \ln w_{n'} + \sum_n \delta_n \ln w_n \ln y + \frac{1}{2}\varepsilon (\ln y)^2 + v + u \tag{18}$$

Where C represents the total cost, w_n and $w_{n'}$ represents input prices, n and n' represent two specific inputs, y represents the output. In our case, y stands for loans and securities. v is the statistical noise term, following a normal distribution, u represents cost inefficiency in the production process, following a non-negative distribution and time-invariant model. Here, α_0, α_n, β, $\gamma_{nn'}$, δ_n, and ε are the parameters to be estimated.

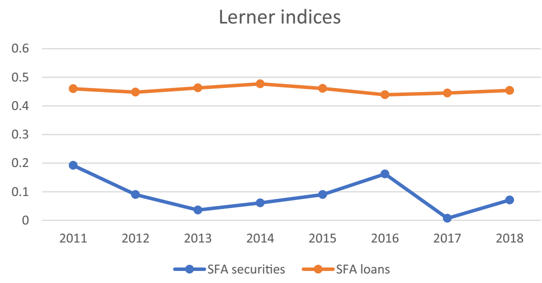
The marginal cost is calculated as:

$$MC = \frac{C}{y} \times \left(\beta + \sum_n \delta_n \ln w_n + \varepsilon \ln y \right) \tag{19}$$

Please see Fig. 10 below regarding the Lerner indices derived from the above calculations. We can see that the levels of market power in the loans market and the securities market are much lower than the estimated derived from our original approach, we find the similar finding showing that Chinese banks have higher levels of market power on loans compared to the ones of securities.

Moreover, we compared its banking results with those derived from the model in Fukuyama and Tan (2022a). Their approach employs a deterministic DEA framework to estimate marginal costs and the Lerner index, providing a baseline for assessing market power in the banking sector. While both methods

Fig. 10 Lerner indices based on stochasic frontier analysis



aim to quantify market power, our Bayesian approach incorporates probabilistic inference, offering greater flexibility in addressing uncertainty and variability in the data. In terms of the Lerner index for the whole Chinese banking industry, we observed that we further expand the analysis of Fukuyama and Tan (2022a) by analysing the level of market power in a multi-output context. The empirical part of Fukuyama and Tan (2022a) is based on a single output context, while the method was developed for a multi-output setting there.

Our results show that Lerner index in the loans market is stable across the examined period, while there is relatively a higher level of volatility in the market power of the securities market. The level of volatility in market power in the securities market is similar to the one reported in Fukuyama and Tan (2022a), although the latter used total assets as the output. In term of market power for different ownership types of Chinese banks, Fukuyama and Tan (2022a) reported that among different bank ownership types, joint-stock commercial banks have relatively the strongest volatility in market power across the period, while although we used different outputs, our results also show the largest variation of Lerner indices for this ownership type. Another difference between the results of ours and those of Fukuyama and Tan (2022a) lies in the fact that we reported significance levels of marginal cost in the Chinese banking industry, whereas the one reported by Fukuyama and Tan (2022a) is quite small.

From a policymaking perspective, our approach enhances the interpretability and applicability of market power estimates in several ways. The Bayesian framework allows regulators to quantify the uncertainty associated with estimated market power levels, facilitating more informed decision-making regarding competition policies and banking regulations. Moreover, by distinguishing between market power in loans and securities, our findings provide policymakers with targeted insights into the competitive dynamics of different banking services. This distinction is crucial for designing regulatory interventions that balance financial stability with market efficiency. In contrast, Fukuyama and Tan (2022a) treated the banking sector as a monolithic entity, limiting the applicability of their findings to policy decisions that require a sectoral or service-specific focus.

6 Conclusion

The Chinese government and financial regulatory authorities had been engaging in the process of interest rate liberalization since 1993 and the process was completed in 2013 and 2015, when the interest rate on loans and the one on deposits were liberalized. Having no upper limit on the deposit interest rate and no lower limit on the loan interest rate was supposed to create a more competitive market. How to enhance market power to make themselves competitive enough was the challenge faced by the bank managers.

The investigation on the market power related topics in the economic sector in general and in the banking industry specifically has not stopped over the last decade, with specific efforts made to investigate this issue from different perspectives. The theoretical investigation seems to be even more important due to the consideration that a precise measurement of market power will provide a solid foundation to examine the importance/influence of market power.

The original Lerner index was widely used for market power measurement and various advancements have been proposed to develop this method theoretically. The current study contributes to the literature in a significant way by proposing a Bayesian likelihood-based approach to measure the marginal cost, which is an important component in calculating Lerner index. Our innovative proposed method benefits from the advantage of handling multiple outputs in a natural way. In addition, the value of posterior means of marginal cost will never be zero. In addition, the proposed method can not only get the marginal cost, but also can obtain the efficiency scores. More specifically, we extend the nonparametric DEA work of Fukuyama and Tan (2022a) by recognizing the necessity of the statistical interpretation under the case of multiple inputs and outputs and our proposed approach benefits from the ability to measure input and output weights, as well as marginal cost and Lerner index from the perspective of statistical uncertainty, through which the uncertainty about the quantities of interest can be quantified.

The findings show a higher market power in loans than the one in securities, which is evidenced also in general by different bank ownership types except the foreign banks, for which we observe a stronger volatility of market power in loans and securities. The findings show that the highest market power in loans and the lowest market power in securities is possessed by the city banks, while the state-owned commercial banks possess the lowest market power. It is observed that foreign banks possess the strongest market power after 2014, with state-owned, joint-stock and rural banks following afterwards. Finally, we observed a level of volatility in bank efficiency. This volatility is also observed for all the different bank types. We cannot see any clear pattern in the level of efficiency among different bank types.

6.1 Broader economic and regulatory challenges

The results from this study provide a useful prism through which to assess broader economic and regulatory challenges that banking systems are facing globally. One such important issue is the trade-off between promoting competition and ensuring financial stability. The high market power of loans among Chinese banks-especially city banks-means that an improvement in profitability and resilience could come with the cost of reduced innovation and efficiency. This trade-off shows up in economies undergoing financial liberalization, as regulators seek to balance competitive pressures with policies aimed at developing a robust banking sector. Efficiency volatility emphasis in this study rhymes with the challenges the world is facing on economic uncertainty, technological disruption, and sustainable finance. In many countries, banks are increasingly forced to operate in rapidly changing digital and regulatory landscapes, including but not limited to the adoption of Basel III standards, climate-related financial disclosures, and data protection regulations. The findings point to the dire need for banks to ring in operational agility for better efficiency and sustainability of external shocks, whether it be economic meltdown or geopolitical conflicts.

Besides, the variation in market power among different bank ownership types has raised some regulatory questions of equity and inclusiveness. For instance, smaller banks or rural institutions usually compete at a disadvantage with larger players due to resource constraints or regulatory burdens. The policymakers in developing and developed economies should ensure that regulatory frameworks do not create disproportionate disadvantages for such entities, given their very important roles in financial inclusion and local economic development. The study also illustrates how bank sector dynamics can be brought more in line with general macroeconomic objectives. Improved market power and efficiency, for example, would presumably help banks allocate credit more highly to productive sectors of the economy, which could raise growth and lower systemic risk. These are valuable insights, especially in the global context of financial integration, where regulators face the added challenge of cross-border banking operations and where variations in market power and efficiency may produce systemic vulnerabilities.

This research finally points to the interaction of financial regulation and innovation. The lower market power of securities among Chinese banks, along with the better performance of foreign banks, reflects the difficulties that domestic banks encounter in adapting themselves to non-traditional financial products. This is a microcosm of the broader struggle to integrate fintech and other technological advancements into regulatory frameworks that balance stability with the fostering of innovation. This balancing act is very important for governments and central banks to undertake in light of the new forms of competition and risks brought about by the rapid evolution of financial technologies. Interpreting the results through these two lenses deepens our contribution to ongoing debates on how the development of financial systems can respond to the interconnected challenges of competition, stability, inclusion, and innovation in an increasingly changing global environment.

6.2 Practical relevance and managerial implications

The findings of this study on market power and efficiency levels among different bank types and financial products have significant practical and managerial implications. These implications can provide valuable insights for the banking industry and individual banks in navigating market dynamics effectively.

Bank managers can use the insights into varying levels of market power across products, such as loans and securities, to optimize resource allocation. For instance, the high market power observed in loans, particularly for city banks, suggests that banks should prioritize improving operational efficiencies and capital allocation in this product line to sustain their competitive edge. Conversely, the lower market power in securities presents an opportunity for banks, especially domestic ones, to develop specialized expertise, reduce marginal costs, and improve economies of scale in this sector. At the same time, efficiency levels across bank types exhibit volatility, emphasizing the need for sustained operational improvements. Managers should invest in advanced risk management systems to reduce inefficiencies, reevaluate cost structures, and foster a culture of continuous improvement by benchmarking performance metrics against more efficient banks or sectors.

The findings also have broader policy implications. The disparities in market power among different bank types and products indicate a need for regulators to promote fair competition. Differentiated support mechanisms could help address the specific challenges faced by various bank types. For instance, policies targeting city banks might mitigate risks associated with high market power in loans by incentivizing diversification into other financial products. The study underscores the importance of adopting customer-centric strategies. Foreign banks demonstrate higher market power in securities, often attributed to their specialized expertise and customer-focused approach. Domestic banks could emulate these practices by offering tailored financial products and strengthening customer relationships through innovative digital banking solutions. Furthermore, the lower demand for securities products among domestic customers highlights the need to enhance financial literacy and educate customers about the benefits of diverse financial products. Banks can also develop marketing strategies that address customer risk aversion while emphasizing the potential returns of securities.

Human capital development is another critical area highlighted by the study. Skilled personnel play a pivotal role in non-traditional banking sectors. Therefore, banks should invest in training programs to enhance employee competencies in areas like securities trading and risk assessment. Establishing knowledge-sharing platforms with foreign banks could facilitate the exchange of best practices, while recruitment strategies should focus on attracting individuals with expertise in emerging areas. These efforts would particularly benefit domestic banks aiming to expand into non-traditional banking products.

Finally, the study points to the need for long-term sustainability in the banking sector. The observed volatility in market power and efficiency levels suggests that banks must adopt strategies prioritizing stability. Diversifying product portfolios can help mitigate risks associated with over-reliance on specific products or customer segments. Implementing robust governance frameworks can further ensure sustainable growth. Additionally, adopting advanced technologies, such as artificial intelligence and big data analytics, can enhance operational efficiencies and provide deeper insights into market dynamics and customer behaviour.

6.3 Implications for competition and efficiency in other emerging markets

The fact that this study finds such variation in market power, especially between loans and securities and across different bank types, has important implications for competition and efficiency in other emerging markets. Many emerging economies face similar challenges to China, with the need to balance financial sector liberalization with the stability and inclusivity of their banking systems. These can also be factored into policy frameworks and managerial strategies in these contexts. Several countries in emerging markets, such as India, Brazil, and South Africa, therefore find a similar type of ownership structure as in China-there are few large state-owned banks and also smaller private or rural ones-which again indicates that the potentially lower market power among the Chinese state-owned banking institutions could therefore still generalize into those countries when the state generally allows social missions to override financial performance. Policymakers in these contexts might consider reforms that would rationalize governance, enhance cost efficiency, and make state-owned banks more competitive with private and foreign banks.

The relative market power differences between traditional products such as loans versus more specialized products such as securities also reflect certain trends in other emerging markets. More often than not, domestic banks cannot compete in these markets for non-traditional financial services due to a lack of expertise, technological constrains, or regulatory barriers. Drawing on the lessons from China's banking sector, this could be achieved through investment in personnel training, investment in digital infrastructure, and strategic partnerships with foreign institutions to enable emerging market domestic banks to expand their capabilities in higher-value-added financial services. The findings also point out the need for a trade-off between competition and efficiency in financial markets. In many emerging economies, greater competition—sometimes as a result of financial inclusion policies—has led to unexpected consequences, such as reduced profitability and riskier lending standards. Policymakers can use this study in the search for means of encouraging healthy competition that retains efficiency, such as differential approaches to bank regulation by size and ownership. These might include tailored prudential requirements or diversification incentives for alternative products whose design achieves competitive parity at lower levels of systemic risk.

The volatility in the efficiency among Chinese banks reflects more poignantly the higher level of challenge faced by the emerging markets to handle economic shocks, changes in regulation, and technology disruption. Other emerging market economies, relying highly on the export of commodities or having geopolitical uncertainties, could benefit from similar strategies emphasizing long-term stability. This would involve the adoption of sound risk management practices, leverage on big data analytics for value resource allocation, and build resilience via diversification. The study thus draws on parallels from the Chinese banking sector to other emerging markets, underlining the importance of customized strategies that address local challenges while leveraging shared insights. Future comparative studies could further validate these implications by exploring market power and efficiency dynamics across diverse regions and institutional frameworks.

In terms of future research, the Bayesian likelihood-based approach proposed in the current study can be further extended by considering multiple stages in the production process. The resultant new estimation of Lerner indices can be compared to the ones of the current study. In addition, additional extensions can be made to consider the undesirable outputs in the production process within the proposed framework of the current study. No matter which aspect of future extensions will be focused on, one of the main issues that needs to be solved is to find relevant data about the output prices.

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