A new way to estimate market power in banking

Abstract

Market power in banking is very important to increase a bank's competitive power. The investigation of this is of particular relevance to the Chinese banking industry in the light of the stability issue experienced by the Chinese commercial banks in 2019. Instead of using translog cost function or semi-parametric method as a component to estimate Lerner index, this study estimates Lerner index based on data envelopment analysis. The results show that joint-stock banks have the lowest market power, while although city commercial banks have a higher level of market power than joint-stock commercial banks, it is still lower than the other three ownership types. Overall, the Chinese banking industry experienced a decline in the level of market power from 2010-2015, after which there was a slight increase in the level, the market power ended up with a value of 0.937 by the of 2018. We notice that the Chinese banking industry in general has a higher level of market power with the value of Lerner index achieved more than 0.93 for every year of the examined period.

Keywords: Data envelopment analysis; Banking; Developing Countries; Lerner index

1. Introduction

One of the main challenges faced by banks is derived from the rise of internet technology, including mobile banking. This reduces the level of market power of the traditional banks; whether this reduction in the level of market power is good or not for banks is unclear from the literature because lower levels of market power will induce banks to undertake higher levels of risk, as reflected by the competition-instability hypothesis (Keeley, 1990). On the other hand, lower levels of market power will result in a lower level of risk-taking behaviour, as represented by the competition-stability hypothesis (Boyd and DeNicole, 2005). Although we are not clear about the influence of market power on bank stability, what we can ascertain is that higher levels of market power will increase bank competitiveness. Banks with higher levels of market power have the ability to make the price of the financial products in the market without reduce the market shares they hold. This, on the one hand, will post threat the existing banks with lower levels of market power due to the fact that low price set by the banks with higher levels of market power will probably lead to a loss of the banks if the price is lower than the cost. On the other hand, the price making strategies of the banks with higher levels of market power will have the effect of preventing the potential banks enter into the market. In summary, because of higher levels of market power, the banks will use pricing strategies in a flexible way to make themselves occupy a good position in the market, which enhances their competitiveness. There are few studies which have already addressed the issue of market power in the banking industry using the Lerner index (Casu and Girardone, 2009; Liu et al., 2014). More recently development of Lerner index includes a scale-corrected Lerner index (Spierdijka and Zaourasa, 2018), and Tsionas et al. (2018) evaluate the Lerner index as a function of the firm's revenue and the output elasticity of its cost.

The banking sector contributes significantly to the country's economy in China by effectively channeling funds from savers to lenders. According to the data provided by the World Bank and China banking and insurance supervision commission, the total assets of banking institutions in China in 2018 account for 23.62% of GDP, an increase from 23.52% in the previous year. Because of the importance of this specific financial sector for the economy, the Chinese government and relevant regulatory authorities had taken steps to reform the industry with the purpose of improving bank performance, increasing the level of competition and promoting bank stability. This includes the write-off of non-performing loans, capital injection, introduction of foreign strategic investors and consistent efforts to liberalise the interest rate on loans and deposits. The Chinese banking sector has received global attention over recent years because of the risk-taking behaviour of the Chinese commercial banks. In 2019, the China banking and insurance regulatory commission took actions on three Chinese commercial banks (Baoshang Bank, Jinzhou Bank and Hengfeng Bank) due to their extreme high level of risk exposure[1]. This is, supposedly, the negative side effect of increases in the competitive condition in the Chinese banking sector, although the initial purpose of this initiative was to improve the performance of Chinese banks. In order to deal with increasing competition among Chinese commercial banks and reduce the level of risk, Chinese commercial banks should increase their level of market power, from which to further improve bank competitiveness. Looking at the level of market power in the Chinese banking industry will, therefore, be of relevance and significance; more specifically, examining the level of market power for different bank types will provide information to the regulatory authority to make effective policies.

The current study is the first to apply the non-parametric data envelopment analysis to estimate market power and to further evaluate the level of market power using a sample of Chinese banks over the period 2010-2018. The findings suggest that Chinese banking industry has a high level of market power. In addition, joint stock commercial banks have the lowest level of market power, followed by city commercial banks.

2. Literature review on the estimation of market power in the banking industry

The Lerner (1934) index was developed originally by an American economist, Abba Lerner, in 1934. The Lerner index is defined and calculated as the difference between price and marginal cost, the proceed of which is further used to divide by the price level to obtain the Lerner index. The value of Lerner index ranges from 0 to 1 with higher values indicating higher levels of market power. In terms of the application of this indicator to the banking sector, the price of banking output is measured by the ratio of total revenue to total assets (Tan and Floros, 2013); the second component of the Lerner index, marginal cost, is measured by the empirical literature under the translog cost function (Tan, 2016). The Lerner index is a victim of its own criticism. It is argued that the Lerner index is unable to identify the source of the deviation of price level from the marginal cost, whether this deviation is from the efficient use of scale or from the need to cover fixed costs (Elzinga and Mills, 2011).

In addition to the traditional Lerner index applied to the banking sector, as discussed before, a number of extensions have been made. Based on Koetter et al., (2012), Clerides et al. (2015) propose an efficiency-adjusted Lerner index. The range of values of this new Lerner index is the same as that of the original Lerner index and both of them have the same indication regarding the values of the index. With regard to the estimation of marginal cost, they differentiate their method to the traditional translog cost function by using a flexible semi-parametric methodology. They argue that production technology for different banks across the industry can be varied and also the production technology can be different over the period, which means the parametric estimation of marginal cost lacks accuracy. Clerides et al.

1 Baoshang and Jinzhou bank are city banks, and Hengfeng is a joint-stock bank.

(2015) still use the cost function, while the difference lies in the fact the estimation of the cost function is conducted through the semi-parametric partial linear smooth coefficient model (Delis et al., 2014).

Besides the efficiency adjusted Lerner index proposed above, Spierdijka and Zaourasa (2018) developed a scale-corrected Lerner index. Two different cases have been identified according to banks' cost function and output level, including increasing marginal cost and U-shape marginal cost, therefore, the authors argue that it would be inappropriate to calculate the Lerner index using marginal cost. Instead, the scale-corrected Lerner index is defined as the difference between the observed price level and the minimum-average cost level. Similar to the efficiency adjusted Lerner index, they also use the translog cost function to derive the Lerner index.

The marginal cost in the Lerner index has been defined by Tsionas et al. (2018) as the elasticity of cost with respect to the specific output. In order to derive this, rather than relying on specific cost functions, as conducted in the previous empirical studies, a nonlinear system of simultaneous equations is estimated. This system-of-equations approach benefits from the advantages of being able to derive the cost efficiency and scale elasticity at the same time, the latter of which can be further employed to derive the Lerner index.

3. Notation and methodology

3.1 Lerner index

Let $\mathbf{x}=(x_1,...,x_N)$ be a non-negative vector of N inputs and let y be a positive scalar output. The production function is denoted by $f(\mathbf{x})$ and the cost function is by

$$C(y,\mathbf{w})=\min_{\mathbf{x}}\left\{\mathbf{wx}\middle|\ f(\mathbf{x})\geq y\right\} \tag{1}$$

where $\mathbf{w}=(w_1,...,w_N)$ is a positive vector of N input prices and $\mathbf{wx}$ is the inner product representing total cost. Using the cost function (1), the "Lerner index" (Lerner 1934) is denoted by

$$L=\frac{p-MC}{p} \tag{2}$$

where p represents the output price and MC is the firm's marginal cost, i.e., the partial derivative $\partial C(y,\mathbf{w})/\partial y$.

3.2 Data envelopment analysis implementation

This section shows how we calculate the Lerner index using DEA. Charnes et al. (1995) argue that there are two advantages of DEA over stochastic frontier analysis (SFA). First, DEA works particularly well with small samples. Second, multiple inputs and outputs stated in different measurement units can be handled by DEA, which doesn't assume functional form of unknown technology. Assume that there are J firms to be assessed. Let $\mathbf{x}_j = (x_{1j},...,x_{Nj})$ and y_j be the observed input vector and the observed scalar output, respectively. Let $\boldsymbol{\lambda} = (\lambda_1,...,\lambda_J)$ be a nonnegative vector of J intensity variables. Then the DEA cost function satisfying variable returns to scale (VRS), is constructed by

$$C(y,\mathbf{w}) = \min_{\mathbf{x},\boldsymbol{\lambda}} \left\{ \sum_{n=1}^{N} w_n x_n \left| \begin{array}{l} \sum_{j=1}^{J} \mathbf{x}_j \lambda_j \le \mathbf{x};\ \sum_{j=1}^{J} y_j \lambda_j \ge y; \\ \mathbf{x} \ge \mathbf{0};\ \sum_{j=1}^{J} \lambda_j = 1;\ \boldsymbol{\lambda} \ge \mathbf{0}. \end{array} \right. \right\} \tag{3}$$

where $\mathbf{0}$ represents an appropriate dimensional vector of zeros. The sum of the intensity variables is equal to $\sum_{j=1}^{J} \lambda_j = 1$, yielding that the technology allows for increasing, decreasing and constant (CRS) returns to scale. If the constraint $\sum_{j=1}^{J} \lambda_j = 1$ is deleted, then the cost function exhibits CRS globally. The dual multiplier form of (3) is written as

$$\max_{\mathbf{v},u,\omega} \left\{ uy + \omega \,\middle|\, -\mathbf{v}\mathbf{x}_j + uy_j + \omega \le 0,\ \forall j;\ \mathbf{v} \le \mathbf{w};\ u \ge 0;\ \omega\ free. \right\} \tag{4}$$

where $\mathbf{v} = (v_1,...,v_N)$. In order to interpret the multipliers in Eq. (4), it is useful to formulate the

Lagrange function[2]

$$\ell(\mathbf{x},\boldsymbol{\lambda},\mathbf{v},u,\omega)=\mathbf{wx}-\sum_{n=1}^{N}v_n\left(x_n-\sum_{j=1}^{J}x_{nj}\lambda_j\right)-u\left(\sum_{j=1}^{J}y_j\lambda_j-y\right)-\omega\left(\sum_{j=1}^{J}\lambda_j-1\right) \tag{5}$$

Since we can write the left-hand side of (5) at the optimum,

$$\ell(\mathbf{x}^*,\mathbf{v}^*,u^*,\omega^*)=C(y,\mathbf{w})=\mathbf{wx}^*-\sum_{n=1}^{N}v_n^*\left(x_n^*-\sum_{j=1}^{J}x_{nj}\lambda_j^*\right)-u^*\left(\sum_{j=1}^{J}y_j\lambda_j^*-y\right)-\omega^*\left(\sum_{j=1}^{J}\lambda_j^*-1\right) \tag{6}$$

where the star * indicates optimality in (5). So, using the envelope theorem, we obtain

$$\frac{\partial C(y,\mathbf{w})}{\partial y}=u^*\geq 0 \tag{7}$$

indicating the optimal multiplier variable u^* in Eq. (4) represents marginal cost. Since $\sum_{j=1}^{J}y_j\lambda_j^*-y\geq 0$, $u^*\geq 0$ and $u^*\left(\sum_{j=1}^{J}y_j\lambda_j^*-y\right)=0$ from the Karush-Kuhn-Tucker conditions (see Bazaraa et al., 2010), we have

$$\begin{cases}\sum_{j=1}^{J}y_j\lambda_j^*-y>0 \;\Rightarrow\; u^*=0\\ \sum_{j=1}^{J}y_j\lambda_j^*-y=0 \;\Rightarrow\; u^*>0\end{cases} \tag{8}$$

Eq. (8) indicates that we can identify whether or not the bank under assessment has market power in the product market. If there is a slack in the output constraint in (3) at the optimum, then the marginal cost equals zero. If the output constraint is tight at the optimum, then marginal cost is strictly positive.

4. Data and multiplier output estimates

We collected the data from 38 commercial banks operating in China over the period 2010-2018. We further classify the banks in the sample into five groups: city commercial banks, rural commercial banks, foreign banks, state-owned commercial banks and joint-stock commercial banks. The data is

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[2] If the cost function is not differentiable, then we can obtain the subdifferential characterizations for the interpretation purpose because the optimal multipliers are the coefficients of the supporting hyperplane. Use of the Lagrange function for the interpretations of the DEA technical efficiency measures is conducted by Førsund (1996). The equivalence between the Lagrange multipliers and the DEA multipliers for Eq. (4) can be established by following the procedure of Fukuyama (2000).

collected from Fitch Connect database.

Regarding the input and output selections, we use three inputs: fixed assets, deposits and personnel expenses following Sealey and Lindley, 1997; Boscia et al., 2009; Ouenniche and Carrales, 2018; three related input prices: the price of funds measured by the ratio of total interest expenses to total deposits (Tan and Floros, 2018), the price of capital, measured by the ratio of non-interest expenses to fixed assets (Maudos et al., 2002), and the price of labour, measured by the ratio of personnel expenses to total assets (Weill, 2004). Total assets are regarded as one single output. The related output price for total assets is calculated by the ratio of sum of total cost and profit to total assets.

Table 1 shows the descriptive statistics of inputs, outputs and their related prices. We can see that, there is a bigger difference in terms of the amount of total deposits compared to the other two inputs. This is mainly attributed to the fact that Chinese banks have substantial differences in bank size. We can also see that Chinese banks have the biggest difference in the price of labour. This correctly reflects one of the main issues in the Chinese banking industry, which is the large disparity in salary of chairman or directors among different ownership types of Chinese banks (Tan, 2019). The table further reports that the largest difference is observed related to total assets, while the Chinese banks have smaller differences in terms of the output price.

<<Table 1---about here>>

5. Results

When we estimate the multiplier model, the solver provides one set of multipliers and such a set is not generally unique. Hence, the estimated marginal cost is not unique. In the single output case, if the bank is interested in enhancing market power, then it is reasonable to minimize the multiplier u related to the output. In this case we use its lower bound estimate (please see Figure 1), which is unique in a single output case, as explained in the text. It is observed that joint-stock commercial banks have the highest level of marginal cost, this explains the lowest level of market power, as reflected by Figure 2. While it is further noticed that state-owned commercial banks have higher levels of marginal cost than the one of city commercial banks, this is in contrast with the comparison of market power of these two ownership types, shown in figure 2 that city commercial banks have lower levels of market power than the one of state-owned banks. This reflects the fact that state-owned commercial banks have even higher price levels, the price level difference between state-owned banks and city commercial banks is larger than the difference in the level of marginal cost of these two ownership types. For a comparison purpose, we also report the upper bound estimate for the year 2018 (Table 2). According to the table in Table 2, three out of the 32 banks exhibit a divergence between the upper and lower bounds. Among the entire 352 $(=32\times11)$ banks, sixteen (one) banks had a zero marginal cost according to the lower (upper) bound estimates.

<<Figure 1--- about here>>

<<Figure 2---about here>>

<<Table 2---about here>>

In this empirical application, we use the lower bound estimate as the output multiplier to obtain the Lerner index. Figure 3 show the results of Lerner index in the Chinese banking industry between 2010-2018. We can see that the Chinese banking industry experienced a consistent decline in the level of market power from 2010 up to 2015, after which the Lerner index was observed to have another increase, through a small volatility, the value of the Lerner index ended up with a value of 0.937 by the end of 2018. Overall, it is noticed that the Chinese banking industry has a high level of market power with the value of Lerner index in each year reached more than 0.93. This shows that that the market is far from perfect or near-perfect competition.

<<Figure 3---about here>>

Alternate solutions typically appear in any DEA multiplier models. The current study only considered estimating the Lerner index under the single output case (total assets as bank output), although the two outputs consisting of loans and securities can be used to estimate the cost function. In spite of this fact, we focus on the single output case as is presented, because of the following two considerations: 1) we tend to think that use of only two outputs related to loans and securities investment is not sufficient due to the fact that each bank's revenue comes from other sources as well, in which case it is difficult to estimate another (third) output and its revenue from the dataset; 2) model building to consider the multiple outputs in the analysis of Lerner index under DEA requires a justification on the estimation procedure and it is outside of the current scope of the paper. More specifically, when the parametric cost function (for example, quadratic form) is used, it imposes a structure on the production technology and the estimated output (shadow) prices may tend to be nonzero when the estimated parameters are nonzero. For the conventional DEA cost function, however, such a structure is not imposed and hence some estimated output prices (multipliers) can be zero. For a rational (cost minimizing or profit maximizing) bank, the marginal costs may not be zero (although it is possible to be zero for some outputs) for the circumstance when the sustainable bank wishes to produce several outputs. Thereby, it is reasonable to attempt to find the positive marginal costs for more than one output, where the output vector of the cost function should be on the corresponding cost frontier and the estimated multipliers are closely related to a specific hyperplane (facet). Alternatively speaking, in order to have positive output multipliers for all outputs, the projected outputs must be on the strongly efficient cost frontier. Clearly, finding relevant multipliers for an empirical analysis requires the theoretical basis and hence we would need to provide the valid procedure that requires a good production theoretical justification.

Moreover, the estimated multipliers should be justified from the empirical/behavioral perspectives. Implementing these issues into empirical analysis requires quite a bit of efforts. The multiple output result provided in Appendix A1 is theoretically valid and we are aware of the importance of implementing multiple outputs. Hence, we think this issue deserves a separate and further analysis but such an analysis is beyond the scope of the current study, the aim of which is to show, as a short article, how DEA can be used to estimate the Lerner index for the Chinese banking industry.

6. Discussion

Tan et al., (2017) uses total assets as the single output and estimate the level of market power in the Chinese banking industry using a translog cost function. In order to make a comparison between our study and Tan et al. (2017), we apply the method adopted by Tan et al. (2017) using our database and check the similarities and differences of the results. More specifically, the models we estimate following Tan et al. (2017) is:

$$LnCost_{it} = \alpha_0 + \alpha_1 LnAssets_{it} + \frac{1}{2}\alpha_2(LnAssets_{it})^2 + \sum_{j=1}^{3}\beta_{itj}LnInput_{itj} + \sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{itjk}LnInput_{itj}LnInput_{itk} + \sum_{j=1}^{3}\gamma_{itj}LnAssets_{it}LnInput_{itj} + \varepsilon_{it} \quad (9)$$

Ln represents natural logarithm, Cost denotes total cost, I and t represent a different bank operating at a specific year, Assets are the bank's total assets, Input represent the input price considered in the study, there are three input prices, they are price of funds, measured by the ratio of interest expenses to total deposits; price of capital, measured by the ratio of non-interest expenses to fixed assets; and price of labour, measured by the ratio of personal expenses to total assets. J and k represent different input prices. The estimated coefficients of the above equation will be used to estimate the marginal cost:

$$MC_{it} = \frac{Cost_{it}}{Assets_{it}}(\alpha_1 + \alpha_2 LnY + \sum_{j=1}^{3}\gamma_{itj}LnInput_{itj}) \quad (10)$$

MC represents marginal cost, Y is total assets, α_1, α_2 and γ_{itj} are the coefficients estimated from the above cost function. Finally, through the calculation of marginal cost, the Lerner index can be further estimated as:

$$Lernerindex_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \quad (11)$$

P is the price, which is calculated as the ratio of revenue (sum of total cost and profit) to total assets.

The results of Tan et al. (2017) are presented in Figure 4. Compared between figure 2 and figure 4, we notice that in general, for all different ownership types of Chinese banks, the Lerner index from our proposed model generates higher values. We noticed that although the Lerner index generated from both of these two models have the highest value in foreign banks, our proposed model shows that the highest Lerner index is obtained by foreign banks in 2010, which reaches 0.963, in comparison, the model based on Tan et al. (2017) has the highest value of Lerner index exhibited by foreign bank in 2014, the value of which is 0.94. Finally, we notice that our proposed model shows that the difference of market power obtained by different ownership types is smaller than the one based on Tan et al. (2017).

Figure 5 shows the marginal cost of different bank ownership types based on the model of Tan et al. (2017). The results show that the joint-stock commercial banks have the highest level of marginal cost, this is in line with the lowest market power of this ownership type, as reflected in Figure 4, while we further noticed that in general, the city commercial banks have lower marginal cost than joint-stock commercial banks, but higher than all the other ownership types. this mainly explain the lower market power of this ownership than joint-stock commercial banks, but higher market power than all the other ownership types. Although there are small differences in the level of marginal cost among state-owned commercial banks, rural commercial banks and foreign banks, we do not observe big differences in the level of market power among these three ownership types. This is attributed to the price difference among them.

<<Figure 4--- about here>>

<<Figure 5--- about here>>

7.Conclusion

The current study is the first to estimate the bank marginal cost using a non-parametric data envelopment analysis. Our results show that the Chinese banking industry experienced a decline in the level of market power from 2010-2015, after which there was a slight increase in the level, the market power ended up with a value of 0.937 by the of 2018. We notice that the Chinese banking industry in general has a higher level of market power with the value of Lerner index achieved more than 0.93 for every year of the examined period. Our results show that, joint-stock commercial banks and city commercial banks have relatively lower levels of market power compared to other bank ownership types. This also coincides with the stability event which took place in 2019. We suggest that:

1) the banking reforms in China should be carefully reconsidered in terms of its aims. The aims to improve the performance and enhance bank stability are reasonable, while it is recommended that increasing the level of competition should be reconsidered and revised to increase the level of market power because this can facilitate the achievement of the previous two aims (improve bank performance and enhance bank stability);

2) the joint-stock banks in China should further enhance their level of market power through financial innovation, which can be facilitated by its own advantage of collaborating with its foreign counterparts in the operation.

Before concluding, let us state future extension possibilities. First, when the input-output data are heterogeneous, the DEA estimates of Leaner index raise two statistical problems. First, the problem of heteroscedasticity arises when the data set comprises several clusters rather than one and the variances are not constant across the clusters. Second, it relates to different production units having varying sizes that are widely dispersed in different size groups. If the size distribution of production units can be viewed in terms of distribution of inputs and outputs, and the dispersion around mean (variance) is assumed to measure the heterogeneity of size variation, then running of DEA models with the variance-adjusted input and output data greatly reduces the problem of heteroscedasticity. Therefore, one area of future research is to use the variance-adjusted inputs and outputs to check the robustness of our results.

Second, although DEA works particularly well with small samples, as discussed previously, it is well known that DEA does not have much discriminant power when the sample is small (relative to the number of inputs and outputs) and that its discriminant power increases as the sample size increases. In the future research, it is recommended that the sample can be further expanded to include multiple countries in the analysis, this will not only serve the purpose as a comparison of bank market power among different countries, but it is supposed that using multiple countries under a DEA model will generate more robust results. Alternatively, this issue can be overcome by applying the pure data envelopment analysis model under a two-stage procedure (Charles et al., 2019).

Finally, as discussed in this paper, empirical applications of multiple output Lerner index will be an important extension possibility.

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Figure 1. marginal cost of different bank ownership types under the proposed method

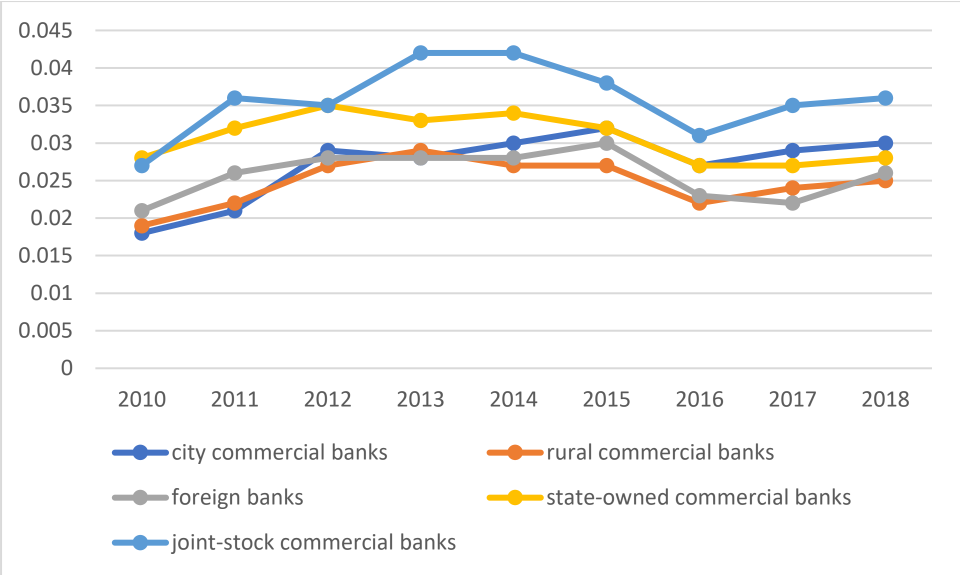

Figure 2. Lerner index for different bank ownership types

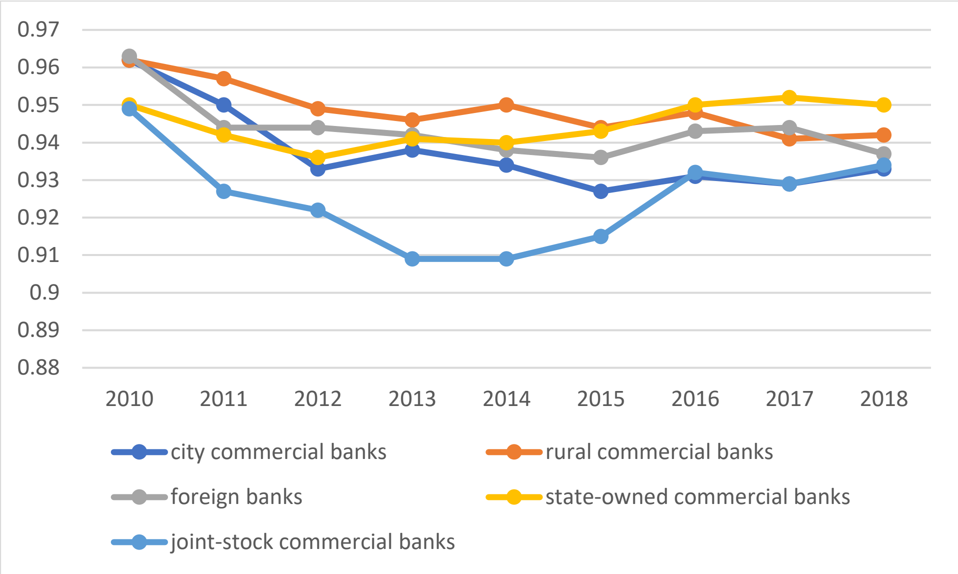

Figure 3. Lerner index of Chinese commercial banks: 2010-2018

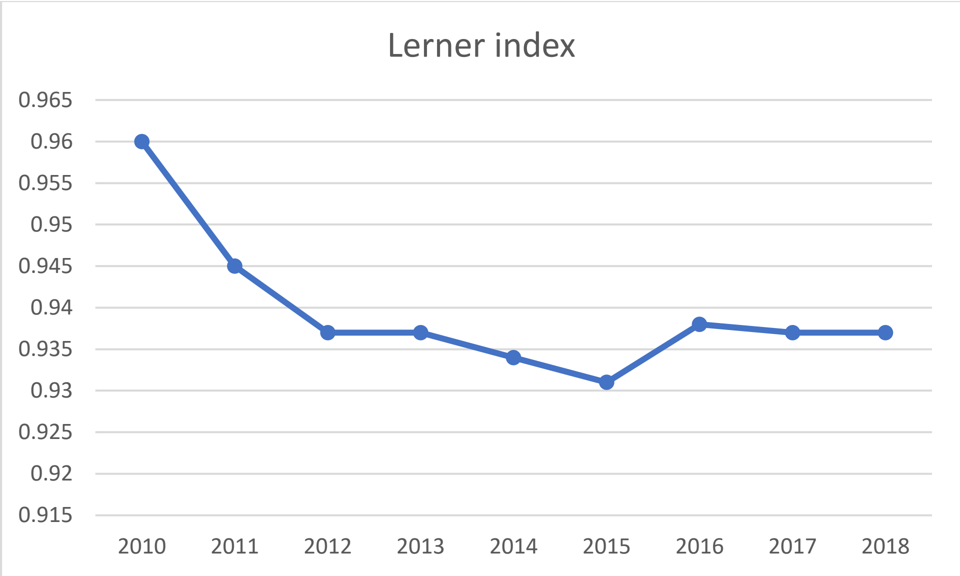

Figure 4 Lerner index with single output (total assets) under translog cost function

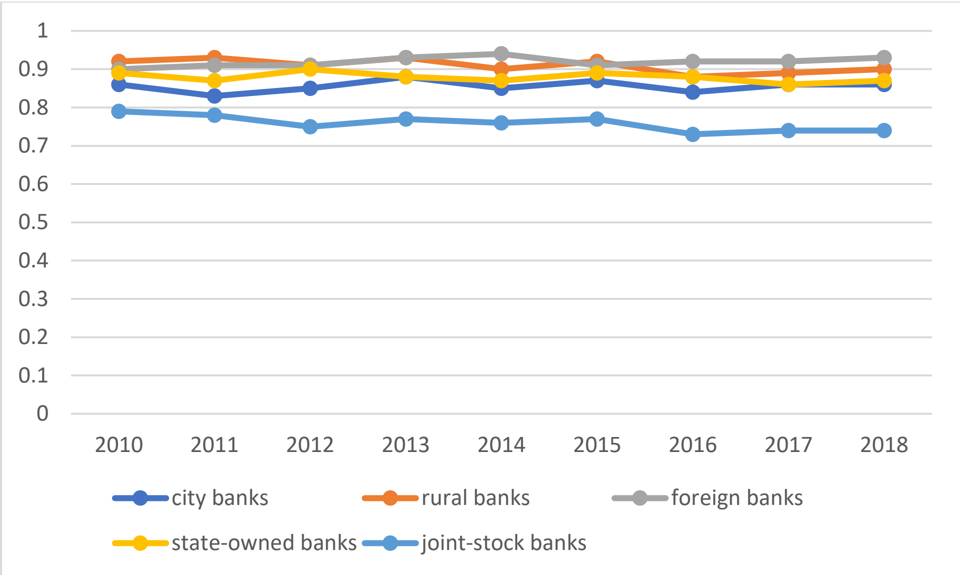

Figure 5. Marginal cost of different ownership types following Tan et al. (2017)

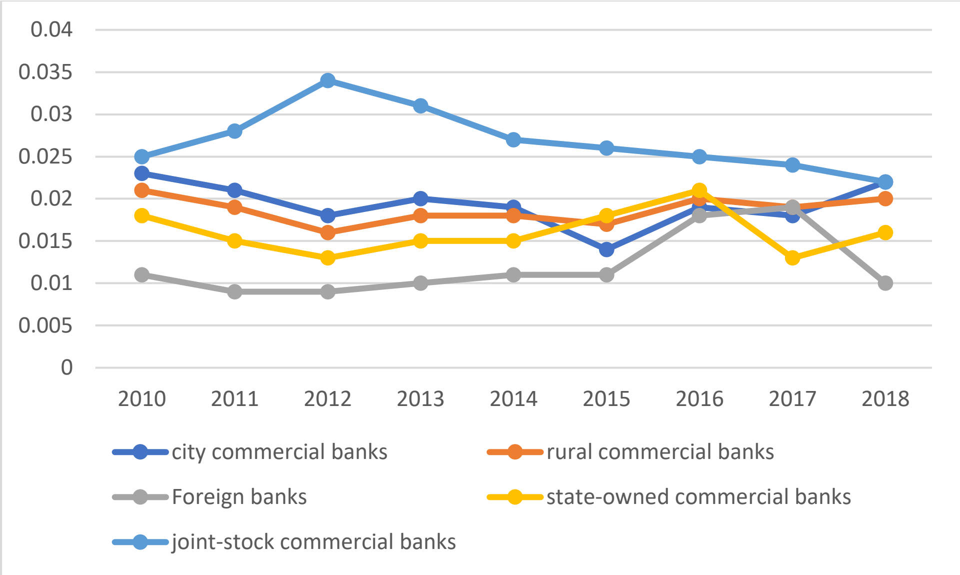

Table 1. Descriptive statistics of the variables

Variables	Observations	Mean	standard deviation	minimum	Maximum
Inputs					
Fixed assets	351	11557.2	29720.5	2.168	145421
Total deposits	351	1647518	3972533	1475.1	$2.23*10^7$
Personnel expenses	351	8951.617	21951.02	24.9	111354
Input prices					
Price of funds	351	0.024	0.008	0.007	0.056
Price of capital	351	0.006	0.003	0.002	0.017
Price of labour	351	6.52	12.75	0.27	120.15
Outputs					
Total assets	351	1927686	4650347	2829.9	$2.61*10^7$
Output prices					
price of assets	351	0.047	0.009	0.033	0.053

Notes: (1) The price of assets is measured by the ratio of sum of total cost and profit to total assets. (2) The units of inputs and outputs are in millions RMB, while both the output and input prices are in ratios.

Table 2: Lower and upper bound estimates of output multiplier for year 2018

bank name	u*	u^{UP}	u^{LW}
Bank of Cangzhou Co., Ltd.	0.02589	0.02589	0.02589
Bank of Chengdu Co., Ltd.	0.03012	0.03012	0.03012
Bank of Dalian Co., Ltd.	0.03394	0.03394	0.03394
Bank of Fuxin Co., Ltd	0.03719	0.03719	0.03719
Bank of Guangzhou Co., Ltd	0.03158	0.03158	0.03158
Bank of Qingdao Co., Ltd.	0.02489	0.02489	0.02489
Bank of Shanghai Company Limited	0.0302	0.03096	0.0302
Bank of Taizhou Co.,Ltd.	0.02675	0.02675	0.02675
Bank of Wenzhou Co., Ltd	0.03217	0.03217	0.03217
Bank of Yingkou Co., Ltd.	0.03474	0.03474	0.03474
Beijing Rural Commercial Bank Co., Ltd.	0.02452	0.02452	0.02452
Citibank (China) Company Limited	0.02579	0.02579	0.02579
Credit Agricole CIB (China) Limited	0	0.04361	0
DBS Bank (China) Limited	0.03772	0.03772	0.03772
Fubon Bank (China) Co., Ltd	0.02646	0.02646	0.02646
Fudian Bank Co., Ltd.	0.02448	0.02448	0.02448
Fujian Haixia Bank Co., Ltd.	0.03083	0.03083	0.03083
Guangxi Beibu Gulf Bank Co., Ltd.	0.02662	0.02662	0.02662
HSBC Bank (China) Company Limited	0.12476	0.12476	0.03247
Hang Seng Bank (China) Limited	0.03904	0.03904	0.03904
Hankou Bank Co., Ltd.	0.03891	0.0389	0.03264
KEB Hana Bank (China) Company Limited	0.03124	0.03124	0.03124
MUFG Bank(China),Ltd.	0.03144	0.03144	0.03144
Metropolitan Bank (China) Ltd.	0	0.00058	0
Mizuho Bank (China), Ltd.	0.02338	0.02338	0.02338
Nanyang Commercial Bank (China) Co., Lt	0.02829	0.02829	0.02829
Shanghai Rural Commercial Bank Co., Ltd	0.02473	0.02473	0.02473
Societe Generale (China) Ltd.	0.03442	0.03442	0.03442
Sumitomo Mitsui Banking Corporation (C	0.02432	0.02432	0.02432
Bank of Beijing Co., Ltd.	0.02987	0.02987	0.02987
Bank of China Limited	0.02828	0.02915	0.02828
Bank of Communications Co., Ltd.	0.03459	0.03459	0.03459
China Construction Bank Corporation	0.02488	0.02488	0.02488
China Everbright Bank Company Limited	0.03596	0.03596	0.03596
China Guangfa Bank Co., Ltd.	0.03454	0.03454	0.03454
Industrial Bank Co., Ltd	0.0359	0.04067	0.0359
Industrial and Commercial Bank of China	0.02569	0.02569	0.02569
Ping An Bank Co., Ltd.	0.03844	0.03844	0.03844
Standard Chartered Bank (China) Limited	0.02683	0.02683	0.02683

Notes: (1) The upper bound and lower bound estimates are obtained as:

$$u^{LW} = \min_{\mathbf{v},u,\omega}\left\{u \mid C^* = uy + \omega, -\mathbf{v}\mathbf{x}_j + uy_j + \omega \le 0,\ \forall j;\ \mathbf{v} \le \mathbf{w};\ u \ge 0;\ \omega\ free.\right\}$$

$$u^{UP} = \max_{\mathbf{v},u,\omega}\left\{u \mid C^* = uy + \omega, -\mathbf{v}\mathbf{x}_j + uy_j + \omega \le 0,\ \forall j;\ \mathbf{v} \le \mathbf{w};\ u \ge 0;\ \omega\ free.\right\}$$

(2) u^* is obtained from Eq. (4).

Appendix A1: Multi-output Lerner index

Let $\mathbf{y} = (y_1, ..., y_M)$ be a vector of M products. The production technology is defined as $T = \{(\mathbf{x}, \mathbf{y}) | \ \mathbf{y} \text{ is producible from } \mathbf{x}\}$ and the multi-product cost function is constructed as $C(\mathbf{y}, \mathbf{w}) = \min_{\mathbf{x}} \{\mathbf{wx} | \ (\mathbf{x}, \mathbf{y}) \in T\}$. If p_m represents the price of product *m* and the marginal cost with respect to product *m* is the partial derivative $MC_m(\mathbf{y}, \mathbf{w}) = \partial C(\mathbf{y}, \mathbf{w}) / \partial y_m$, then a Lerner index for product *m* is obtained as

$$L_m = \frac{p_m - MC_m(\mathbf{y}, \mathbf{w})}{p_m}, \qquad m = 1, ..., M$$

In order to obtain the estimate L_m based on DEA, we replace $u^*\left(\sum_{j=1}^{J} y_j \lambda_j^* - y\right)$ in (6) with $\sum_{m=1}^{M} u_m^* \left(\sum_{j=1}^{J} y_{mj} \lambda_j - y_m\right)$ to obtain $MC_m(\mathbf{y}, \mathbf{w}) = \partial C(\mathbf{y}, \mathbf{w}) / \partial y_m = u_m^*$ which is an optimal multiplier variable m corresponding to product m in the multi-product DEA multiplier model.

In the literature, there are Lerner index expressions for multi-product technology. Shaffer and Spierdijk (2019), for example, presented two kinds of Lerner index. One is the revenue-share weighted Lerner index, denoted as $L = \sum_{m=1}^{M} W_m L_m$ where $W_m = \frac{p_m y_m}{\sum_{m'=1}^{M} p_{m'} y_{m'}} = \frac{R_m}{R}$, $R = \sum_{m'=1}^{M} R_{m'}$ and L_m is the *m*-th output Lerner sub-index. The other is an aggregate Lerner index $L^{Agg} = \frac{p^{Agg} - MC(y, \mathbf{w})}{p^{Agg}}$, where $p^{Agg} = \frac{\sum_{m=1}^{M} p_m y_m}{y}$, $y = \sum_{m=1}^{M} y_m$ and $MC(y, \mathbf{w}) = \partial C(y, \mathbf{w}) / \partial y$. The aggregate Lerner index L^{Agg} adds all different products to obtain the aggregate output and is similar to the single output case as is presented in the main text.