The impacts of innovation and trade openness on bank market power: the proposal of a minimum distance cost function approach and a causal structure analysis

Hirofumi Fukuyama[1,*], Mike Tsionas[2], Yong Tan[3,*]

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[1] Department of Business Management, Faculty of Commerce, Fukuoka University, 8-19-1 Nanakuma, Jonan-ku, Fukuoka, 8140180, Japan

*corresponding author: fukuyama@fukouoka-u.ac.jp

[2] Montpellier Business School & Lancaster University Management School, LA1 4YX, UK

[3] School of Management, University of Bradford, Bradford, West Yorkshire, UK, BD7 1DP

Abstract

This study estimates output market power in the Chinese banking industry using the multi-output Lerner index. We propose a minimum distance cost function approach, which allows us to determine not only the level of market power but also the non-profit maximizers and efficiency level of Chinese banks. Following the first-stage analysis, we employ the generalized method of moment system estimator to evaluate the impacts of bank innovation and trade openness on market power in a multi-output banking context. In particular, we innovatively propose a causal structure analysis based on Wang and Blei (2019) to validate and verify the robustness of our results. We also assess this relationship for different types of bank ownership in China. The findings suggest that Chinese banks exhibit high market power in loans. Furthermore, the results show that bank innovation and trade openness have a significant negative impact on market power in loans, but a significant positive impact on market power in securities. The results also indicate a significantly negative impact of trade openness on overall market power. We find that higher levels of innovation among state-owned and joint-stock commercial banks improve the overall level of market power. The results suggest that, for all bank ownership types, trade openness has a significant negative impact on market power in loans but a significant positive impact on market power in securities. The impact on the overall level of market power is consistently significant and negative.

Keywords: Data envelopment analysis; Foreign direct investment; Multi-output Lerner index; Chinese banks; Causal relation; Least distance

1. Introduction

The Lerner index, which represents market power and is a function of output quantities, is typically estimated using a parametric cost function that requires the pre-specification of a parametric form. It is widely used, along with other indicators, to measure market power or the competitive conditions in various economic sectors (Kim and Lyn, 1986; Genesove and Mullin, 2001; Elzinga and Mills, 2011). Alternatively, the Lerner index can be estimated without any parametric specification of the unknown technology by employing nonparametric data envelopment analysis (DEA), which utilizes a multiplier form of the DEA cost function (multiplier cost function). Fukuyama and Tan (2022) demonstrate how to estimate a DEA-based multi-output Lerner index by exploiting the equivalent result that marginal costs are equal to the output multipliers. However, their empirical DEA analysis was limited to a single output situation. While the multi-output version is theoretically a straightforward extension of the single output approach, the standard multiplier-based cost function tends to generate zero-valued output multipliers, indicating a pure monopoly. Additionally, it is known that the multiplier cost function provides only one of the optimal solutions. Taking these factors into consideration, Fukuyama and Tan (2023) present an empirical procedure for estimating the multi-output Lerner index. They apply this procedure to the Chinese real estate industry, assuming that all firms are profit maximizers.

While a pure monopoly is theoretically possible in monopolistic markets, it is crucial to determine the practical relevance of estimated zero values. To address this issue, we propose a novel minimum distance procedure for estimating the DEA cost function, which serves as the foundation for the multi-output Lerner index. In this procedure, we first identify the cost-efficient banks using the DEA cost function commonly used in economics. Subsequently, we determine a cost-efficient output multiplier vector within a binary linear programming minimum distance framework. To accomplish this, we extend Aparicio et al.'s (2007) minimum distance production approach to incorporate a cost function analysis. Developing this new procedure is necessary since Aparicio et al.'s (2007) approach only requires data on physical input and output quantities, whereas cost function estimation also necessitates input prices.

The present study builds upon the existing work of Fukuyama and Tan (2022, 2023) as the first research endeavor to estimate DEA-based single-output and multi-output Lerner indices. This study not only introduces a DEA estimation procedure for profit-maximizing firms but also incorporates a second-stage regression analysis and a statistical causal structure analysis. The causal analysis is particularly employed to address endogeneity issues and examine the validity of our DEA formulation. We determine the level of market power for individual outputs and multiple outputs in both of these distinct sets. This proposal serves as a benchmark for estimating the Lerner index in a multiple-output context within a DEA framework. Importantly, the minimum distance approach allows us to utilize the strongly cost-efficient projection point for identifying output multipliers, as the straightforward application of the DEA-based cost function does not provide such a projection. While classic non-radial measures aim to identify the "farthest" strongly efficient point for computational convenience, it may be practically challenging for banks to achieve this point when evaluating their efficiency performance. Hence, it is reasonable for bank managers to set a target that requires less effort. In a banking study, Fukuyama et al. (2022b) argue that technology, regulation, and competitive conditions affect banks' scale economies, making it difficult for them to operate at the optimal scale. They reference Mester (2005) to support this claim. In such cases, the minimum distance approach can identify a target that is relatively easy to attain compared to the classic non-radial approach. This is because bank managers prefer to set a realistic and easily achievable target with minimal effort. It is worth noting that the use of the greatest distance measures primarily stems from computational convenience (Fukuyama et al., 2014).

To estimate the Lerner index, it is necessary to derive marginal costs from the weights of the multiplier-form (dual) DEA cost function. Traditionally, the Lerner index has been estimated using a parametric cost function that assumes a pre-specified functional form. However, since the actual functional cost function structure is often unknown to researchers, using a pre-specified form may lead to misleading policy recommendations. In light of this, the current paper adopts a nonparametric method based on DEA (Data Envelopment Analysis), which provides reasonable estimates as long as the multipliers (marginal costs) associated with outputs are positive. The positivity of multipliers is ensured when the projected point lies on the strongly cost-efficient frontier. To identify the positive multipliers, we utilize the least distance procedure introduced by Aparicio et al. (2007), extending it to the cost function. This extension has previously been applied in the competition study of the Chinese real estate sector by Fukuyama and Tan (2023), assuming that marginal costs do not exceed the corresponding output prices. This restriction was necessary in the real estate sector study due to challenges in determining the relative magnitude of marginal costs compared to observed output prices. However, based on previous Chinese banking studies (Tan and Floros, 2013; Fukuyama and Tan, 2022), which indicate that marginal costs are significantly lower than the corresponding output prices, there is no need to employ Fukuyama and Tan's (2023) approach in this study. Therefore, the current study does not impose any restrictions on marginal costs. Instead, we examine whether the banks operated under the condition of profit maximization.

Our results indicate that, overall, the Lerner index based on loans as the sole output is higher than the indices using securities as the output, as well as the multi-output Lerner index. In the loans market, we did not observe a significant difference in the level of market power among different bank types, but joint-stock and state-owned banks displayed the highest volatility. Furthermore, we found that state-owned banks demonstrated non-profit maximization in the securities market in 2012[1]. Comparatively, the securities market exhibited much higher volatility in terms of market power when compared to the loans market. The efficiency derived from the minimum cost distance function reveals that both state-owned commercial banks and joint-stock commercial banks operate at high levels of efficiency. These findings contrast with the results obtained from the accounting ratio (total cost to total assets).

While estimating market power (Lerner index) is important, practical policy implications can only be made by evaluating the determinants of market power. We address a literature gap by being pioneers in examining

[1] In the literature, a negative Lerner index value is thought of as the absence of market power (Spierdijk and Zaouras, 2017).

the impacts of bank innovation and trade openness on market power in a multi-output banking context. Innovation in the Chinese banking sector can be observed in several areas. Firstly, there has been rapid development and adoption of mobile payment systems, with Alipay and WeChat Pay being the main platforms used by the Chinese people. According to statistics from the People's Bank of China, mobile payment transactions in China reached approximately $43.5 trillion in 2020. The use of mobile payment systems benefits banks by reaching more customers and providing convenient services, thereby enhancing their market power. Secondly, the Chinese banking industry has made significant investments in digitalizing banking services, including online banking and digital services. The popularity of online banking enables banks to reduce costs, while customers can manage their accounts, transfer funds, and apply for loans without visiting physical branches. The convenience provided to customers significantly increases customer loyalty, leading to an improvement in bank market power. Thirdly, Chinese banks have actively engaged in partnerships and collaborations with FinTech companies to leverage their expertise in artificial intelligence, big data analytics, and blockchain technology. These collaborations aim to improve operational efficiency, enhance innovation capabilities, and offer personalized financial products and services. This is expected to increase banks' competitive edge and market power. Lastly, the impact of technology giants like Alibaba and Tencent cannot be overlooked. These companies provide comprehensive financial products and services, including digital wallets, online lending, and various financial investment tools. They pose significant challenges and threats to traditional Chinese banks, negatively impacting the establishment and sustainability of market power for these banks.

Trade openness has a significant impact not only on the overall economy but also on various economic sectors, including the banking industry. In the context of the banking industry, the influence of trade openness can be observed from the following perspectives: 1) Foreign bank presence: China has gradually opened its banking industry to foreign banks, reflecting trade openness. According to statistics from the China Banking and Insurance Regulatory Commission, the number of foreign banks operating in China reached 41 as of 2020. The presence and operations of foreign banks in the Chinese banking industry pose significant challenges to the market power of domestic Chinese banks; 2) Market share of foreign banks: The Chinese banking industry not only experiences the presence of foreign banks due to trade openness but also sees an increase in the competitive power of foreign banks in the domestic market. According to a report by Deloitte, the market share of foreign banks increased from 1.5% in 2010 to 2.9% in 2019. This growing market share occupied by foreign banks poses a significant threat to the operations and market power of domestic Chinese banks; 3) Regulatory reforms: In order to facilitate trade openness, relevant policies have been implemented by the Chinese banking and insurance regulatory authorities to remove restrictions on foreign banks. This enables foreign banks to establish branches and expand their operations more easily. These regulatory reforms are expected to increase competition in the Chinese banking industry and reduce the level of market power of domestic Chinese banks; 4) Cross-border financial services: Trade openness facilitates international trade and investment, with the banking industry playing a crucial role in facilitating cross-border provision of financial services. Chinese commercial banks have expanded their operations by establishing branches and subsidiaries overseas, competing with other banks in foreign countries. Similarly, not only have foreign banks established their operations in the Chinese market, but they have also aimed to serve customers from different countries within their domestic markets. This significantly enhances the level of competitive conditions among banks and has a significant impact on the level of market power.

The examination utilizes the two-stage generalized method of moments system estimator. Additionally, we innovatively propose the causal structure analysis of Wang and Blei (2019) in the second-stage analysis to validate and check the robustness of our results. The existing empirical banking literature is limited in terms of examining relevant relationships, as it relies on the application of various econometric techniques. No attempt has yet been made to propose and apply causal structure analysis for this investigation. Therefore, our combination of operational research methods in the first stage and econometric techniques in the second stage, along with the validation and robustness check through causal structure analysis, can be generalized for future studies with a two-stage analysis. This approach involves applying operational research methods in the first-stage analysis of efficiency and second-stage analysis examining the determinants of efficiency. Furthermore, from an empirical banking perspective, we also examine the impacts of trade openness and bank innovation on market power in a multi-output banking context for different bank ownership types. This not only significantly contributes to the banking literature but also provides more concrete policies at the bank-type level.

The current study is structured as follows: Section 2 provides a literature review on DEA in banking and measuring bank market power. Section 3 presents and explains the methods proposed to estimate market power, investigate the impacts of bank innovation and trade openness on market power, and the causal structure analysis. Section 4 covers the data and results, followed by Section 5 discussing additional analysis. Section 6 discusses the policy implications. Finally, concluding remarks are given in Section 7.

2. Literature review

2.1. DEA and its extensions in the banking industry

Data envelopment analysis (DEA) is a widely applied non-parametric estimation method used to evaluate bank efficiency (Antunes et al., 2022). Over time, this non-parametric approach has undergone consistent evolution and development, resulting in various advancements. These advancements include dynamic Network Data Envelopment Analysis (Tan et al., 2021), non-radial directional distance DEA, conditional directional distance approach, and probabilistic directional distance function (Barros et al., 2012; Kevork et al., 2017). Other advancements include Satisficing DEA (Chen et al., 2018), Slack-based measure (multi-stage) super efficiency, and dynamic slack-based measure (Chiu et al., 2011; Wanke et al., 2015). Bootstrapped DEA (Tortosa-Ausina et al., 2008; Aggelopoulos and Georgopoulos, 2017) and Fuzzy DEA and Fuzzy DEA super efficiency (Wanke et al., 2016) have also been proposed.

These applications of DEA and its advancements focus on bank efficiency estimation, but no effort has been made in the previously reviewed studies to address the measurement of marginal cost and market power. Recently, Fukuyama et al. (2023) proposed a dynamic network DEA behavioral model for estimating Chinese bank efficiency. One notable feature of this study is the examination of causal structures based on the data, facilitated by the general deconfounding approach proposed by Wang and Blei (2019). The proposed causal analysis validates the structure of the factors of production in the proposed behavioral model. Fukuyama et al. (2023) contribute to filling one of the gaps in the literature by applying the causal structure analysis by Wang and Blei (2019) to analyze the production factors in the DEA model. This causal structure analysis can also be regarded as an innovative tool applicable to any business-related studies engaging in a second-stage analysis. However, the literature has not yet made this attempt. Utilizing causal structure analysis, along with appropriate econometric techniques, will provide more robust and accurate results.

2.2. Measuring bank market power

The Lerner index has been widely used in measuring bank market power (Jimenez et al., 2013; Aigner et al., 2014) and assessing the influence of market structure on bank stability. Other studies have focused on the relationship between competition and efficiency (Asongu et al., 2019). In addition to these two groups of studies, empirical literature has examined various other relationships, such as competition and cost of credit (Fungacova et al., 2017), bank competition and collateral (Hainz et al., 2013), bank competition and liquidity creation (Horvath et al., 2016), bank competition and credit constraints (Leon, 2015), bank competition and firm's access to finance (Love and Peria, 2015), and bank competition, foreign bank presence, and privatization (Simpasa, 2013). Some studies have solely focused on market power estimation, including extensions of the original Lerner index estimation (Clerides et al., 2015).

The stochastic frontier approach was initially developed by Kumbhakar et al. (2012) and later applied by Coccorese (2014) to measure bank competition. Gischer et al. (2015) argue that the original estimation of the Lerner index requires information about the prices of both outputs and inputs. They proposed a segment-based adjusted Lerner index under the intermediation approach, where loans and deposits are considered as outputs and inputs, respectively. The adjusted Lerner index measures the output price using the average lending rate, while the marginal cost is approximated by the average deposit rate. Linderberg and Ross (1981) and Elzinga and Mills (2011) criticized the original Lerner index for not capturing the deviation of price level from marginal cost. To address this limitation, Spierdijka and Zaourasa (2018) developed a Lerner index that considers the scale effect and applied it to evaluate US bank competition.

Recently, Fukuyama and Tan (2022) used the multiplier (nonparametric DEA) cost function to estimate market power of Chinese banks from 2011 to 2018. While they theoretically demonstrated how to calculate the multi-output Lerner index, their empirical studies focused only on the single-output situation to avoid complexities. The empirical evidence indicated that Chinese banks generally have strong market power across the examined years. Fukuyama and Tan (2023) expanded on the study of Fukuyama and Tan (2022) by estimating marginal cost under DEA in a multi-product context, applying the method to measure market power in the Chinese real estate industry. However, the study assumes that all decision-making units are profit maximizers, which may not reflect the real scenario.

3. Methodologies

3.1 DEA-based Lerner index

Let N and M be the index sets of inputs and outputs respectively, and $|N|$ and $|M|$ represent the respective numbers of the respective index sets. Let the non-negative inputs and outputs vectors be represented by $\mathbf{x} = (x_1, \dots, x_N)^{\mathrm{T}} \in \Re_{+}^{|N|}$ and $\mathbf{y} = (y_1, \dots, y_M)^{\mathrm{T}} \in \Re_{+}^{|M|}$, where the superscript "T" represents the transposition operator. The bank production technology can be expressed as

$$T = \left\{(\mathbf{x}, \mathbf{y}) \in \Re_{+}^{|N|+|M|} \middle| \mathbf{y} \text{ can be produced by } \mathbf{x}\right\}. \tag{1}$$

In this study, we construct the technology (1) using nonparametric data envelopment analysis. Let J be the index set consisting of observed banks and $|J|$ be the number of the observed banks. Each bank j transforms a non-negative input vector $\mathbf{x}_j = (x_{1j}, \dots, x_{|N|,j})^{\mathrm{T}} \in \Re_{+}^{|N|}$ to produce a non-negative output vector $\mathbf{y}_j = (y_{1j}, \dots, y_{|M|,j})^{\mathrm{T}} \in \Re_{+}^{|M|}$. The vector of intensity variables with non-negative values is represented by $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_{|J|})^{\mathrm{T}} \in \Re_{+}^{|J|}$ that serve to form the technology of the banking industry. Then the bank technology is written as

$$T = \left\{(\mathbf{x}, \mathbf{y}) \in \Re_{+}^{|N|+|M|} \middle| \textstyle\sum_{j \in J} \mathbf{x}_j \lambda_j \leq \mathbf{x},\ \sum_{j \in J} \mathbf{y}_j \lambda_j \geq \mathbf{y},\ \sum_{j \in J} \lambda_j = 1,\ \boldsymbol{\lambda} \geq \mathbf{0}\right\} \tag{2}$$

where the convexity constraint $\sum_{j \in J} \lambda_j = 1$ allows for variable returns to scale and the appropriate dimensional vector of zeros are represented by 0. The vector of input prices with positive values is represented by $\mathbf{w} = (w_1, \dots, w_{|N|})^{\mathrm{T}} \in \Re_{++}^{|N|}$ and the total cost c reflecting from the inner product can be expressed as $\mathbf{w}^{\mathrm{T}}\mathbf{x} = w_1 x_1 + \cdots + w_{|N|} x_{|N|} = c$. A nonparametric (or DEA) cost function (Färe, Grosskopf and Lovell, 1994) can be expressed based on the production technology (2) as below:

$$C(\mathbf{y}, \mathbf{w}) = \min_{\mathbf{x}, \boldsymbol{\lambda}} \left\{\mathbf{w}^{\mathrm{T}}\mathbf{x} \middle| \textstyle\sum_{j \in J} \mathbf{x}_j \lambda_j \leq \mathbf{x}, \sum_{j \in J} \mathbf{y}_j \lambda_j \geq \mathbf{y},\ \sum_{j \in J} \lambda_j = 1,\ \boldsymbol{\lambda} \geq \mathbf{0}\right\} \tag{3}$$

Relative to the cost function (3), an m-th output Lerner sub-index L_m denoted as

$$L_m = \frac{p_m - MC_m(\mathbf{y}, \mathbf{w})}{p_m}, \quad m \in M \tag{4}$$

where p_m represents the price of output m and $MC_m(\mathbf{y}, \mathbf{w})$, the partial derivative $\partial C(\mathbf{y}, \mathbf{w}) / \partial y_m$, is the evaluated bank's nonnegative marginal cost with respect to output m and the numerator indicates the markup for output m. To provide the interpretation of Lerner sub-index L_m, consider the following profit maximization problem, $\max_{\mathbf{x}, \mathbf{y}} \left\{\mathbf{p}(\mathbf{y})^{\mathrm{T}} \mathbf{y} - \mathbf{w}^{\mathrm{T}}\mathbf{x} \middle| (\mathbf{x}, \mathbf{y}) \in T\right\}$, can be written as

$$\max_{\mathbf{y}} \left\{\mathbf{p}(\mathbf{y})^{\mathrm{T}} \mathbf{y} - C(\mathbf{y}, \mathbf{w})\right\} \tag{5}$$

Eq. (5) is taken the first-order conditions as below:

$$\frac{p_m - MC_m(\mathbf{y}, \mathbf{w})}{p_m} = -\frac{\partial p_m(\mathbf{y})}{\partial y_m} \frac{y_m}{p_m(\mathbf{y})}, \quad m \in M. \tag{6}$$

For a single product case (M=1), the right-hand side of the latter expression of Eq. (6) becomes the single product inverse demand function. Now, assuming that the price of output m is dependent only upon its own output, in which case $p_m(\mathbf{y})$ is written as $p_m(y_m)$, then the Lerner sub-index for output m equals

$$\varepsilon_m(\mathbf{y}) = \frac{\partial p_m(\mathbf{y})}{\partial y_m}\frac{y_m}{p_m(\mathbf{y})}, \qquad m \in M \tag{7}$$

which is non-positive. If a bank has market power in product market m, then $1 > L_m > 0$, which becomes smaller with decreasing market power[2]. If perfect competition prevails then the bank has no market power, which is the case where L_m=0 with $p_m = MC_m(\mathbf{y}, \mathbf{w})$. The profit maximizing bank's demand function must be elastic, because

$$\left(1 - \frac{MC_m(\mathbf{y}, \mathbf{w})}{p_m}\right) \geq -\frac{1}{\varepsilon_m(\mathbf{y})} \iff \varepsilon_m(\mathbf{y}) \leq -1.$$

It should be noted that if $p_m < MC_m(\mathbf{y}, \mathbf{w})$, then L_m<0, in which case the bank is not maximizing profits[3]. Using this theoretical evidence, we classify the sample banks into two groups: profit maximizing banks and non-profit maximizing banks.

The multiplier form of (3) is

$$\max_{\mathbf{v},\mathbf{u},\omega}\left\{\mathbf{u}^{\mathsf{T}}\,\mathbf{y} + \omega \middle| -\mathbf{v}^{\mathsf{T}}\,\mathbf{x}_j \; + \mathbf{u}^{\mathsf{T}}\,\mathbf{y}_j \; + \omega \leq 0 \;\; (\forall j \in J),\; \mathbf{v} - \mathbf{w} \leq \mathbf{0},\; \mathbf{v} \geq \mathbf{0},\; \mathbf{u} \geq \mathbf{0},\; \omega\text{: free in sign}\right\} \tag{8}$$

The following Lagrangian is formulated to relate the multipliers in Eq. (8) and marginal cost:

$$\begin{aligned}\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \mathbf{v}, \mathbf{u}, \omega) = \mathbf{w}^{\mathsf{T}}\mathbf{x} - \sum\nolimits_{n \in N} v_n \left(x_n - \sum\nolimits_{j \in J} x_{nj}\lambda_j\right) \\ - \sum\nolimits_{m \in M} u_m \left(\sum\nolimits_{j \in J} y_{mj}\lambda_j - y_m\right) - \omega\left(\sum\nolimits_{j \in J} \lambda_j - 1\right)\end{aligned} \tag{9}$$

where v_n and u_m are nonnegative while ω is unsigned.

We write the optimum for the left part of (9) as:

$$\begin{aligned}C(\mathbf{y}, \mathbf{w}) = \mathbf{w}^{\mathsf{T}}\mathbf{x}^* \; - \textstyle\sum_{n \in N} v_n^* \left(x_n^* - \sum_{j \in J} x_{nj}\lambda_j\right) \\ - \textstyle\sum_{m \in M} u_m^* \left(\sum_{j \in J} y_{mj}\lambda_j^* - y_m\right) - \omega^* \left(\sum_{j \in J} \lambda_j^* - \mathbf{1}\right)\end{aligned} \tag{10}$$

The envelope theorem to (10) yields

$$MC_m(\mathbf{y}, \mathbf{w}) = \frac{\partial C(\mathbf{y}, \mathbf{w})}{\partial y_m} = u_m^*, \qquad m = 1, \ldots, M. \tag{11}$$

Fukuyama and Tan (2022) utilized Eq. (11) to study the output market power of the Chinese banking industry using the Lerner index which requires that the output multipliers u_m^* be obtained. Since there are in general alternate optimal solutions in Eq. (8), it is essential to provide a reasonable procedure for the estimation of u_m^*. To do so, we turn to Shephard's (1970) cost-indirect output possibility set[4] denoted by

$$IP(\mathbf{w}/c) = \{\mathbf{y} | C(\mathbf{y}, \mathbf{w}/c) \leq 1\} = \left\{\mathbf{y} \middle| \begin{array}{l}\sum_{j \in J} \mathbf{x}_j \; \lambda_j \; \leq \mathbf{x},\; \sum_{j \in J} \mathbf{y}_j \; \lambda_j \; \geq \mathbf{y}, \\ (\mathbf{w}/c)^{\mathsf{T}} \; \mathbf{x} \leq 1,\; \sum_{j \in J} \lambda_j \; = 1,\; \boldsymbol{\lambda} \geq \mathbf{0}\end{array}\right\} \tag{12}$$

[2] Note that L_m must be less than one because $L_m > 1$ would mean $MC_m(\mathbf{y}, \mathbf{w}) < 0$.
[3] Spierdijk and Zaouras (2017) provide some analysis for behavioural goals other than the profit maximization.
[4] Regarding the use of Shephard's indirect functions, the output market Lerner index was estimated using the output price-restricted framework by Fukuyama and Tan (2023) and the input market Lerner index (rate of exploitation) was estimated by Fukuyama et al. (2022b).

where the positive scalar c is the prescribed total cost and $C(\mathbf{y},\mathbf{w})/c = C(\mathbf{y},\mathbf{w}/c)$ by the positive linear homogeneity of the cost function (3). We follow Färe et al. (1994) and Färe and Primont (1995) for the DEA formulation of (12). Using the cost function and letting c be total observed cost, the overall cost efficiency $(CEff)$ measure is defined by

$$CEff = \frac{C(\mathbf{y},\mathbf{w})}{c} = C(\mathbf{y},\mathbf{w}/c). \tag{13}$$

The cost-efficient bank will have $CEff = 1$, i.e., $c = C(\mathbf{y},\mathbf{w})$. The cost-inefficient bank will have the value of $CEff$ ranging between 0 and 1 i.e., $CEff \in (0,1]$. Let CE be an index set of cost-efficient banks.

Considering $IP(\mathbf{w}/c)$ we develop the following graph-based slack (GBS) DEA model as

$$GBS(\mathbf{y},\mathbf{w}/c) = \max \sum\nolimits_{n\in N} \frac{s_n^x}{2|N|\, g_n^x} + \sum\nolimits_{m\in M} \frac{s_m^y}{2|M| g_m^y}$$

subject to:

$$\begin{gathered} \sum_{j\in J} \mathbf{x}_j\ \lambda_j\ = \mathbf{x}-\mathbf{s}^x\,;\ \sum_{j\in J} \mathbf{y}_j\ \lambda_j\ = \mathbf{y}+\mathbf{s}^y\,; \\ \sum\nolimits_{j\in J} \lambda_j\ = 1;\ \ (\mathbf{w}/c)^{\mathsf{T}}\,\mathbf{x} \le 1;\ \ \mathbf{x} \ge \mathbf{0};\ \mathbf{s}^x\ \ge \mathbf{0}\,; \\ \mathbf{s}^y\ \ge \mathbf{0};\ \ \boldsymbol{\lambda} \ge \mathbf{0} \end{gathered} \tag{14}$$

where $\mathbf{s}^x = \left(s_1^x, \dots, s_{|N|}^x\right)^{\mathsf{T}} \in \Re_+^{|N|}$ and $\mathbf{s}^y = \left(s_1^y, \dots, s_{|M|}^y\right)^{\mathsf{T}} \in \Re_+^{|M|}$ represent excess input surpluses and output shortfalls, respectively. In Eq. (14), $g_n^x > 0$ and $g_m^y > 0$ are the n-th input and m-th output directions and the reciprocal of $2|N|g_n^x$ and $2|M|g_m^y$ represent the weights attached to the n-th input and the m-th output slack, respectively. The number "2" appears because there are two kinds of variables: inputs and outputs.

The dual form of Eq. (14) is given as

$$\max \quad -\mathbf{u}^{\mathsf{T}}\,\mathbf{y} - \omega + \delta$$

subject to:

$$\begin{gathered} \mathbf{v}^{\mathsf{T}}\,\mathbf{x}_j\ - \mathbf{u}^{\mathsf{T}}\,\mathbf{y}_j\ - \omega \ge 0, \qquad j \in J; \\ -v_n\ + \left(w_n\ /c\right)\delta \ge 0\,, n \in M\,; \\ v_n\ \ge \frac{1}{2|N|g_n^x}\ , n \in N;\ \ u_m \ge \frac{1}{2|M|g_m^y}\ , m \in M; \\ \delta \ge 0; \mathbf{v} \ge \mathbf{0};\ \ \mathbf{u} \ge \mathbf{0};\ \ \omega \text{ free.} \end{gathered} \tag{15}$$

Since we have that $\mathbf{v}^{\mathsf{T}}\,\mathbf{x}_j\ - \mathbf{u}^{\mathsf{T}}\,\mathbf{y}_j\ - \omega \ge 0 \Leftrightarrow -\mathbf{v}^{\mathsf{T}}\,\mathbf{x}_j\ + \mathbf{u}^{\mathsf{T}}\,\mathbf{y}_j\ + \omega \le 0$, we define $t_j\ = \mathbf{v}^{\mathsf{T}}\,\mathbf{x}_j\ - \mathbf{u}^{\mathsf{T}}\,\mathbf{y}_j\ - \omega \ge 0$. Then $t_k\ = \mathbf{v}^{\mathsf{T}}\,\mathbf{x}_k\ - \mathbf{u}^{\mathsf{T}}\,\mathbf{y}_k\ - \omega = 0$ for all $k \in CE$.

For a fixed level of $\mathbf{w}/c$, let $\partial_o\ (IP(\mathbf{w}/c))$ be the set of all strongly cost-efficient outputs in $IP(\mathbf{w}/c)$, which dominate the output vector $\mathbf{y}_o$ of decision-making unit (DMU) "o". Assume that the positive directions[5] $g_n^x\ (n \in N)$ and $g_m^y\ (m \in M)$ satisfy (16g) and (16h). Based on Eqs. (14) and (15), we solve the following minimum distance graph-based slack ($mdGBS(\mathbf{y}_o\ ,\mathbf{w})$) model using mixed integer linear programming:

$$\max \quad \sum\nolimits_{n\in N} \frac{s_n^x}{2|N|\ g_n^x} + \sum\nolimits_{m\in M} \frac{s_m^y}{2|M| g_m^y} \tag{16\_obj}$$

Subject to:

$$\sum\nolimits_{k\in CE} x_{nk}\lambda_k = x_n - s_n^x, \qquad n \in N; \tag{16a}$$

$$y_m = \sum\nolimits_{k\in CE} y_{mk}\lambda_j = y_{mo} + s_m^y, \qquad m \in M; \tag{16b}$$

$$1 = \sum\nolimits_{k\in CE} \lambda_k\ ; \tag{16c}$$

$$(\mathbf{w}/c)^{\mathsf{T}}\ \mathbf{x} \le 1; \tag{16d}$$

$$-\sum\nolimits_{n\in N} v_n x_{nk} + \sum\nolimits_{m\in M} u_m y_{mk} + \omega + t_k = 0, \qquad k \in CE; \tag{16e}$$

$$-v_n + \left(\frac{w_n}{c}\right)\delta \ge 0, \qquad n \epsilon N; \tag{16f}$$

$$v_m \ge \frac{1}{2|N| g_n^x}, \qquad n \in N \tag{16g}$$

$$u_m \ge \frac{1}{2|M| g_m^y}, \qquad m \in M \tag{16h}$$

$$\lambda_k \le \mathbb{M} b_k, \qquad t_k \le \mathbb{M}(1 - b_k), \qquad k \in CE \tag{16i}$$

$$\sum\nolimits_{n\in N} v_n = 1 \tag{16j}$$

$$\mathbf{w}^{\mathsf{T}}\mathbf{x} \ge \mathbf{u}^{\mathsf{T}}\ \mathbf{y}_o + \omega \ge \varepsilon \tag{16k}$$

$$b_k : \text{binary variable for } k \in CE \tag{16l}$$

$$\mathbf{x} \ge \mathbf{0}, \mathbf{s}^x \ge \mathbf{0}, \mathbf{s}^y \ge \mathbf{0},\ \boldsymbol{\lambda} \ge \mathbf{0}, \delta \ge 0, \mathbf{v} \ge \mathbf{0}, \mathbf{u} \ge \mathbf{0} \tag{16m}$$

where $\mathbb{M}$ is a positive quantity, ε is a positive number, and CE is an index set of strongly cost-efficient DMUs. The estimation system of equations consisting of (16) and (16a)-(16m) provides the estimates of output multipliers within a minimum distance setting (minimization of slacks) of bank "o". This estimation system extends the production-based one given in Aparicio, Ruiz and Sirvent (2007) into Shephard (1970)'s cost-indirect production function setting. We normalize multipliers $v_n\ (n \in N)$ as Eq. (16h), because not only ω and

[5] The relative sizes of directions are of significance rather than the absolute values, and hence we can choose any units of measurement.

t_k $(k \in CE)$ are decision variables in Eq. (16*e*) and δ in Eq. (16*f*) is a decision variable but also $\mathbb{M}$ is a prespecified positive number in Eq. (16*i*). For some normalization of multipliers in a production-based context of minimum distance, see for example Zhu et al. (2018). See also Zhu et al. (2018) and Fukuyama, Matousek and Tzeremes (2022b) for alternative direct production-based methods. The first inequality part of Eq. (16*k*) comes from the linear programming cost function duality between the cost function (3) and its multiplier form (8) for a given level of $\mathbf{w} \in \Re^N_{++}$, since $\min(\mathbf{w}^\top \mathbf{x}) = \max(\mathbf{u}^\top\ \mathbf{y}_o\ + \omega)$ implies $(\mathbf{w}^\top \mathbf{x}) \geq (\mathbf{u}^\top\ \mathbf{y}_o\ + \omega)$ for $(\mathbf{x}, \mathbf{y}) \in T$. The second inequality part of Eq. (16*k*) ensures ε is a sufficiently small positive number so that the multiplier-based cost is positive. Clearly, the existence of ε diallows the zero value of the multiplier-based cost. The term $2|M|g^y_m$ in the constraints represents a lower bound of output multiplier u_m. The input target and the output target vectors from (16) are obtained as $\mathbf{x}^* = \sum_{k \in CE} x_{nk}\lambda^*_k + \mathbf{s}^{x*}$ and $\mathbf{y}^* = \sum_{j \in E} \mathbf{y}_j\ \lambda^*_j$, respectively, where * indicates the optimality.

Next adapting Fukuyama and Sekitani (2012), we obtain an appropriate value of $\mathbb{M}$ for the computational purpose. Observe that $-\mathbf{v}^\top \mathbf{x}_j + \mathbf{u}^\top \mathbf{y}_j + \omega \leq 0\ (\forall j \in J)$ and $\mathbf{v}^\top \mathbf{x}_j - \mathbf{u}^\top \mathbf{y}_j - \omega = t_j$ from (16e). Since t_j =0 for $j \in CE$ and $\sum_{n \in N} v_n = 1$, we have that $\omega = \mathbf{v}^\top \mathbf{x}_j - \mathbf{u}^\top \mathbf{y}_j \geq \min\{x_{nj} | n \in N,\ j \in CE\} - \mathbf{u}^\top \mathbf{y}_j$, equivalently, $-\min\{x_{nj} | n \in N,\ j \in CE\} \geq -\mathbf{u}^\top \mathbf{y}_j - \omega$. Using this result along with the definition of t_j yields $0 \leq t_j = \mathbf{v}^\top \mathbf{x}_j - \mathbf{u}^\top \mathbf{y}_j - \omega \leq \mathbf{v}^\top \mathbf{x}_j - \min\{x_{nj} | n \in N,\ j \in CE\} \leq \max\{x_{nj} | n \in N,\ j \in CE\} - \min\{x_{nj} | n \in N,\ j \in CE\} \leq \mathbb{M}$. We use $\mathbb{M} = \max\{x_{nj} | n \in N,\ j \in CE\} - \min\{x_{nj} | n \in N,\ j \in CE\}$ in our estimation.

Remark 1: We utilize the objective function expression (16_*obj*) by viewing the formulation as an extension of the directional distance function due to Chambers, Chung and Färe (1996, 1998) in the sense that the directional distance function is defined with respect to the direction vectors: $\mathbf{g}^x = \left(g^x_1, \dots, g^x_{|N|}\right)^\top \in \Re^{|N|}_+$ and $\mathbf{g}^y = \left(g^y_1, \dots, g^y_{|M|}\right)^\top \in \Re^{|M|}_+$. The objective function represented by $\sum_{n \in N} \frac{s^x_n}{2|N|\, g^x_n} + \sum_{m \in M} \frac{s^y_m}{2|M| g^y_m}$ is used by Fukuyama and Weber (2009), who examined how various direction vectors are associated with the directional distance functions as well as various forms of slack inefficiency (equivalently "Russell measures" due to Färe and Lovell,1978).

Remark 2: In the axiomatic production analysis given in Shephard (1970) and further elaborated by Färe and Primont (1995), the quasi-convexity of the cost function is not guaranteed, and neither is the convexity of the cost-indirect output possibility set $IP(\mathbf{w}/c)$, i.e., the conventionally employed regularity conditions (properties) on the production technology are not sufficient to ensure its convexity. However, the DEA-based output possibility set is convex, hence the DEA cost function is quasi-convex. Clearly, the convexity of $IP(\mathbf{w}/c)$ and the quasi-convexity of $C(\mathbf{y}, \mathbf{w}/c)$ in $\mathbf{y}$ are equivalent, because $\mathbf{y} \in IP(\mathbf{w}/c) \Leftrightarrow C(\mathbf{y}, \mathbf{w}/c) \leq 1$ by construction.

Remark 3: Eq. (16) contains all constraints of GBS model (14) and its dual form (15). Eq. (16) provides target values of inputs and outputs based on the cost function, which is a set of all outputs satisfying $C(\mathbf{y}, \mathbf{w}/c) = 1$. This is so because $IP(\mathbf{w}/c)$ is the set of all outputs satisfying the cost function value being less than or equal to c.

Remark 4: Since Eqs. (3) and (8) form a linear programming duality, we can obtain $u_m^*\left(\sum_{j=1}^{J} y_{mj}\lambda_j^* - y_{mo}\right) = 0$, where $u_m^* \geq 0$ and $\sum_{j=1}^{J} y_{mj}\lambda_j^* - y_{mo} \geq 0$. So, the strong complementary slackness conditions between output m and the corresponding multiplier yield the following:

$$\left(u_m^* > 0 \ \Rightarrow \ \sum_{j\in J} y_{mj}\lambda_j^* - y_{mo} = 0\right) \text{ and } \left(u_m^* = 0 \ \Rightarrow \ \sum_{j\in J} y_{mj}\lambda_j^* - y_{mo} > 0\right). \tag{17}$$

It should be emphasized that Eq. (17) holds in Eq. (16) since Eq. (16) estimates the cost function indirectly by means of the indirect output possibility set (12).

Remark 5: The framework (16) is in line with Aparicio, et al. (2007), who developed for the direct production framework without using observed prices. Note that their minimum distance formulation is originally developed to find an input-output projection point in a minimum distance framework. In our case, we try to find a projection vector of production variables as well as a vector of multipliers which is consistent to Pareto-Koopmans efficiency.

A revenue-weighted output-market Lerner index can be defined by using the revenue shares $\mathcal{W}_m$ as weights for sub-indexes L_m

$$\text{Lerner index} = \sum_{m\in M} \mathcal{W}_m L_m \tag{18}$$

where $\mathcal{W}_m = p_m / \sum_{\acute{m}\in M} p_{\acute{m}}\, y_{\acute{m}}$ and p_m are the revenue share and price of output m, respectively.

As noted earlier, Eq. (8) is highly degenerate, i.e., there are many possible sets of optimal solutions related to multipliers ($\mathbf{v}$, $\mathbf{u}$, ω) in (8). We wish to restrict the solution sets further by employing Eq. (16), in which a nonzero divergence between $\mathbf{w}^{\mathsf{T}}\mathbf{x}$ and $\mathbf{u}^{\mathsf{T}}\,\mathbf{y} + \omega$ is allowed. To narrow the divergence, we introduce a two-step estimation procedure as follows:

Step 1: We first minimize the difference given the constraints of (16) to obtain a minimum difference. That is, we solve

Min $CDiff = \mathbf{w}^{\mathsf{T}}\mathbf{x} - \mathbf{u}^{\mathsf{T}}\,\mathbf{y} - \omega$ s.t. all the constraints in Eq. (16).

to obtain the estimate of the optimal objective function, labelled $CDiff^*$. Hence, $CDiff^*$ is an allowable difference between the primal cost function and the multiplier-based cost function.

Step 2: Using $CDiff^*$ as a lower bound and appending the constraint $\mathbf{w}^{\mathsf{T}}\mathbf{x} - \mathbf{u}^{\mathsf{T}}\,\mathbf{y} - \omega \geq CDiff^*$, we obtain the least distance model by minimizing the weighted input-output slacks, $\sum_{n\in N}\frac{s_n^x}{2|N|\,g_n^x} + \sum_{m\in M}\frac{s_m^y}{2|M|g_m^y}$.

Remark 6: Fukuyama et al. (2023) estimate input market power based on the revenue function (in contrast to our cost function). The input market power index is an extension of Robinson's (1933) rate of exploitation, which corresponds to the Lerner index in the input market where labor is the input. The estimation of the input market power index in Fukuyama et al. (2023) is done within a least distance framework by identifying the closest strongly revenue-efficient point. Hence, the study of Fukuyama et al. (2023) and the current study are related to each other. An alternative to the nonparametric cost and revenue function analysis (Fukuyama and Tan, 2022, 2023; Fukuyama et al., 2023) is Polemis and Tzeremes's (2019) probabilistic regression approach of nonparametric frontier analysis, which examines competition conditions in U.S. manufacturing sectors. Polemis and Tzeremes (2019) formulate sectoral productive efficiency by considering the effects of market structure (concentration levels) in a directional distance function setting. It is important to note that the nonparametric probabilistic approach utilizes information derived from the data to determine the predictor without assuming a parametric form for the relationship between predictors and dependent variables. However, the nonparametric probabilistic approach requires larger sample sizes compared to standard regression based on parametric models. Furthermore, Polemis and Tzeremes (2019) assume that the production frontier is probabilistic from the outset, whereas our study assumes a deterministic cost frontier. As far as we know, there has been no formal introduction of probabilistic cost frontier models that extend Polemis and Tzeremes (2019) in the minimum distance DEA literature. Therefore, such an analysis would be a potential future extension but lies beyond the scope of the current study.

3.2 Analysis on the determinants of bank market power

Not only do we contribute to the literature by investigating bank market power from an innovative operational research perspective, but we also address gaps in the empirical literature by examining the determinants of bank market power. Previous studies that investigate the determinants of market power primarily focus on the overall level of market power, without considering the differences across different banking markets. Furthermore, no study has evaluated the impact of bank-level innovation and trade openness on bank market power. Our study aims to fill these gaps. The examination of the determinants of bank market power is outlined as follows:

$$Lerner_{it} = C + \alpha_1 Lerner_{i,t-1} + \sum_{j=1}^{j} \alpha_2 X_{it}^{j} + \alpha_3 Macro_t + v_{it} + \mu_{it} \quad (19)$$

Lerner represents the Lerner indices in loans, Lerner indices in securities, and the weighted Lerner indices derived from the first-stage analysis. "i" and "t" stand for a specific bank operating in a specific year. "C" is the constant term, and α_1, α_2, and α_3 are the coefficients to be estimated. "X" represents the bank-level determinants, including bank size, bank capitalization, bank diversification, and the market share of two different assets: loans and securities. The choice of these bank-specific determinants is in line with Efthyvoulou and Yildirim (2014) as well as Fernández de Guevara et al. (2005). However, these studies only focus on the overall market power and do not investigate market power in different banking markets. Additionally, we control for another bank-specific determinant, which is bank innovation, proxied by the ratio of intangible assets to total assets. Several research works have assessed the influence of competition on innovation (Bos et al., 2013). In the area of banking and innovation, attempts have been made to investigate the impact of financial innovation on bank growth in assets, loans, and profits (Lee et al., 2020). Another study examines the impact of the active use of credit derivatives on bank behavior (Norden et al., 2014). The findings suggest that banks with larger gross positions in credit derivatives charge lower corporate loan spreads. Scott et al. (2017) find that the adoption of digital innovation (i.e., adoption of SWIFT) has a large and long-term effect on bank performance. While most studies focus on the banking sector, there are also innovation-related studies that investigate relevant issues in other economic sectors.

For example, using data from the Chinese chemical drug industry over the period 1991 to 2000, Li and Vermeulen (2021) find that innovation through introducing new products is associated with lower average firm profitability. Demirel and Mazzucato (2012), using pharmaceutical firms in the US, find that the positive relationship between research and development and firm growth is only exhibited for small firms, while there is a negative relationship for large firms.

No effort has been made yet to investigate the impact of innovation on firm market power in general, particularly in the banking context. However, there is a potential relationship between them, considering the fact that innovation is known to be helpful in reducing marginal costs (Sen and Tauman, 2007), which could increase market power. The causal relationship between these two factors has also been discussed by Pleatsikas and Teece (2001). Intangible assets have been found to positively contribute to both firm and industry-level productivity (Marrocu et al., 2012). In the banking industry specifically, Koetter and Noth (2013) find a positive correlation between bank productivity and banks' markups. The ratio of bank intangible assets to total assets plays a significant role in determining market power in both the loans segment and securities segment of the banking industry. A higher ratio indicates the presence of valuable non-physical assets such as brand reputation, customer relationships, and technological expertise. This ratio can have a positive impact on market power in loans through factors like differentiation, customer loyalty, and competitive advantage. These intangible assets contribute to market power by attracting a larger customer base, fostering trust, and offering superior securities products and services. A higher ratio of intangible assets signifies a bank's ability to stand out in the securities market, gain a competitive edge, and exert greater market power. Based on the previous findings regarding the positive impact of intangible assets on productivity, as well as the positive influence of productivity on markups, and taking into account the theoretical discussions, we propose the following hypotheses:

H1: the impact of bank innovation on market power in loans is significant and positive

H2: The impact of bank innovation on market power in securities is significant and positive

H3: the impact of bank innovation on overall bank market power is significant and positive.

In addition to the bank-specific determinants, we also consider a macroeconomic determinant, which is trade openness. Trade openness, characterized by the liberalization and integration of international trade, has significant implications for market power in both the securities segment and loans segment of the banking industry. Trade openness facilitates access to international capital, allowing banks to diversify their funding sources and invest in technology and product development. This enhanced access to capital strengthens their market position and may contribute to increased market power in securities. However, trade openness in the banking sector can also bring challenges and potential negative effects on market power in loans. One significant aspect is the intensified competition that arises with the entry of foreign banks into domestic markets. These foreign banks often have advantages such as lower-cost funding and advanced technology, which put domestic banks at a disadvantage and reduce their market power in loans. The impact of trade openness on the level of market competition has been evaluated by Kim (2000) in terms of the manufacturing industries, and the influence of trade in services on carbon efficiency has been examined by Feng et al. (2022). The impact of trade openness on competition in the financial services sector has also been investigated by Zhang et al. (2015). However, these studies have limitations: 1) they did not specifically investigate the banking sector, but rather examined the whole financial institutions; 2) they focused on assessing the condition of competition without explicitly evaluating the level of market power; 3) the competition measurement is solely reflected by the concentration of deposits held by state-owned institutions, which has limitations in terms of scope and accuracy.

Starting with the loans market, the Chinese Banking and Insurance Regulatory Commission (CBIRC) simplified bureaucratic procedures for lending to state-owned enterprises, foreign-invested enterprises, collectively-owned enterprises, and private enterprises (PREs). Medium and small-sized commercial banks, as well as foreign banks, were encouraged to provide credit support to these entities. As a result, the level of competition in the loans market increased, leading to a reduction in the level of bank market power. In addition to traditional banking credits offered by different types of Chinese banks, trade openness also involves the provision of non-traditional banking services, such as letters of credit and documentary collections (Niepmann and Schmidt-Eisenlohr, 2017a). Using the United States as a case study, Niepmann and Schmidt-Eisenlohr (2017b) argue that smaller banks specialize in specific markets for providing letters of credit. However, the market share of the top five banks steadily rose from 2017 to 2012. We believe this scenario is also applicable to the Chinese banking industry. Large-scale state-owned commercial banks and joint-stock commercial banks mainly provide these types of services, while some smaller banks lack sufficient experience in conducting this business, resulting in lower involvement in issuing letters of credit. Even if smaller banks engage in this type of business, they are less competitive due to the economies of scale and scope enjoyed by the larger state-owned and joint-stock commercial banks. Consequently, we argue that the demand for letters of credit resulting from trade openness will bring significantly higher volumes of business to the larger state-owned and joint-stock commercial banks, which hold much larger market shares compared to the smaller banks. Based on these arguments, we have formulated the following hypotheses:

H4: the impact of trade openness on market power in loans is significant and negative

H5: the impact of trade openness on market power in securities is significant and positive.

H6: trade openness on the overall bank market power has a significantly positive or negative effect depending upon whether it has a stronger/weaker impact on market power in securities compared to the one on market power in loans. If the negative impact derived from the loans market is bigger, the overall influence would be significantly negative, while if the impact derived from the loans market is smaller, the overall influence would be significantly positive.

We applied the generalized method of moments (GMM) two-step estimation for the second-stage analysis since the persistence of market competition should be taken into consideration in the modeling framework (Gilbert and Newbury, 1982). Therefore, we used one lagged period of the Lerner index as the first independent variable, where the coefficient in α_1 in (19) represents the speed of adjustment. To address the issue of endogeneity, we treated market share in securities and bank size as endogenous variables in the GMM estimation. We used the second lag of market share in securities and the second lag of bank size to address endogeneity concerns.

Specifically, we used the differenced errors and the first lags of the differences of market share in securities and bank size as instruments for the level errors. The variables used in estimating the Lerner index, as well as the bank-level determinants, were retrieved from the Fitch Connect database. The macroeconomic determinants were obtained from the World Development Indicators, which served as the main source of data.

In addition to the key variables, innovation and trade openness, we also control for several other potential determinants of bank market power, including market share in securities, bank size, bank capitalization, and bank diversification. In the banking industry, the relationship between market share in securities and market power in loans can be examined through the concept of cross-subsidization (Louzis and Vouldiz, 2017). Cross-subsidization refers to the practice of utilizing profits or market power in one product or service to subsidize or influence the pricing and competitiveness of another product or service within the same industry. A bank with a larger market share in securities can potentially enjoy greater market power in that segment. This enhanced market power in securities can provide the bank with additional resources and leverage that it can utilize in other areas, including loans. Bank size plays a significant role in shaping market power in the securities segment within the banking industry. As banks grow in size, they can spread their fixed costs over a larger customer base, resulting in lower average costs per transaction. This cost advantage allows larger banks to offer more competitive pricing and capture a larger market share in securities. The reputation and brand recognition associated with larger banks also contribute to their market power in securities, as investors and clients perceive them as trustworthy and capable. Economies of scale play a role as larger banks can achieve cost efficiencies by spreading fixed costs over a larger lending portfolio, potentially allowing them to offer more competitive loan terms. Bank capitalization is a vital determinant of market power in the loans segment of the banking industry. A well-capitalized bank possesses the financial strength and resilience to support its lending activities and absorb potential losses. Adequate capitalization enables banks to take on more risk, expand their lending capacity, and offer competitive loan terms. This enhances their market power. A well-capitalized bank also possesses the financial resources to invest in technology and talent and establish a strong competitive position in securities-related activities. Adequate capitalization enables banks to undertake securities transactions with confidence, offer a diverse range of securities products and services, and attract clients and investors. This further promotes market power. Diversification allows banks to spread their risks, enhance risk management capabilities, and reduce volatility in securities activities. It also provides additional revenue streams, reducing reliance on interest income and improving financial performance. Moreover, diversification strengthens competitive positioning by offering a comprehensive range of securities products and services, attracting a broader client base, and establishing a reputation for expertise. The market perception of diversified banks as resilient and adaptable further enhances their market power in securities. By offering a comprehensive range of loan products and catering to diverse borrower needs, diversified banks can gain a competitive edge and establish a reputation for expertise. This competitive positioning enhances their market power in loans by capturing a larger market share and attracting borrowers seeking specialized loan solutions.

4. Data and results

This study utilizes data from 80 Chinese banks with different ownership types over the period 2012-2019. Specifically, the sample includes 18 foreign banks, 11 joint-stock banks, 34 city banks, 13 rural banks, and 4 state-owned banks. For the estimation of Lerner indices, we consider three inputs: total deposits, personnel expenses, and fixed assets. Two outputs are used: total loans and securities. The output price of loans is calculated as (interest revenue)/(total loans), while the output price of securities is derived from (non-interest revenue)/(total securities). Data for this study is collected from the Fitch Connect database. Table 1 provides an overview of the variable statistics.

Table 1. Descriptive statistics of the variables used to calculate Lerner indices (unit: RMB million)

Variables	Observations	M	S.D.	Min	Max
Inputs					
Deposits	640	1196239.4	3114390.3	477.6	21254803
Fixed assets	640	8104.46	24850.4	0.9	155480
Personnel expenses	640	6630.48	17901.8	14.7	122487
Input prices					
Deposits	640	0.026	0.007	0.0081	0.071
Fixed assets	640	5.435	10.88	0.26	120.14
Labour	640	0.006	0.003	0.0002	0.03
Single Outputs					
Loans	640	722196.03	1985796.6	57.1	14524454
Total securities	640	373531.1	932437.28	4.79	7235244
Output prices					
Output price of loans	640	0.154	0.124	0.058	1.788
Output price of securities	640	0.099	0.299	0.013	7.21

●M, S.D., Min, and Max represent Mean value, Standard deviation, minimum value and maximum value, respectively.

Table 2 presents the descriptive statistics of the output multipliers, single-output Lerner indices, and the aggregate Lerner index[6]. Observing the table, we can note that the loans output has a higher average value for the output multipliers compared to securities. This suggests that the marginal cost of producing securities in the Chinese banking sector is lower than that of loans. When examining the different Lerner indices, we observe that the Lerner index for loans is the highest, followed by the overall weighted Lerner index, while the Lerner index

6 Throughout the empirical section, the observed input-output vector equals to the input-output direction vector. In this way, the graph-based slack (GBS) model is units-invariant.

for securities is the lowest.

Table 2. Descriptive statistics of observe cost, output specific Lerner indexes, and weighted Lerner index, as well as output multipliers

variables	Obs	Mean	SD	Minimum	Maimum
L_1	640	0.8652	0.1541	0.2176	1
L_2	640	0.723	0.5368	-6.582	0.9999
Weighted L	640	0.8496	0.1468	-0.1943	0.9995
u_1	640	0.0156	0.0163	0.00000004	0.0746
u_2	640	0.0136	0.0545	0.00000004	0.71

●Obs stands for observations, M represents Means, SD is standard deviation, Min and Max are minimum and maximum values. L_1 and L_2 represent Lerner indices in loans and securities, respectively. Weighted L represents the weighted Lerner index. U_1 and U_2 stand for output multipliers in loans and securities, respectively.

We compare the annual observed values and target values of inputs and outputs. Additionally, we calculate the percentage change between these two values. The findings are presented in Table 3. The results indicate that Chinese bank managers should pay more attention to fixed assets as a factor of production, in comparison to deposits and labor. As observed from the table, the largest contraction in fixed assets occurred in 2017, with a percentage change of 18.09%. This was followed by contractions of 14.13% in 2018 and 13.81% in 2019. Overall, the table demonstrates that fixed assets were expected to contract by a significantly higher percentage each year, compared to deposits and labor. Regarding the outputs, the findings suggest that bank managers should prioritize the production extension of securities. This is evident from the fact that, on an annual basis, securities were expected to expand at a much higher percentage compared to loans.

Table 3. Comparison between mean target and observed values of inputs and outputs over 2012-2019

	Inputs			Outputs	
Year	Deposits (x1)	Fixed assets (x2)	Personnel expenses (x3)	Loans (y1)	Securities (y2)
2012					
Target	792931.2	6020.8	5088.6	469791.7	166627.6
Observed	810262.0	6537.2	5168.6	469726.5	163596.4
Percentage change	2.19%	8.58%	1.57%	0.014%	1.85%
2013					
Target	869749.4	6474.3	5365.6	540484.7	209487.1
Observed	898644.9	7288.4	5756.0	530496.2	207111.7
Percentage change	3.32%	12.57%	7.28%	1.88%	1.15%
2014					
Target	969784.9	7060.2	5746.1	604794.5	263732
Observed	995263.3	7944.0	6263.7	594042.3	262438.8
Percentage change	2.63%	12.52%	9.01%	1.81%	0.5%

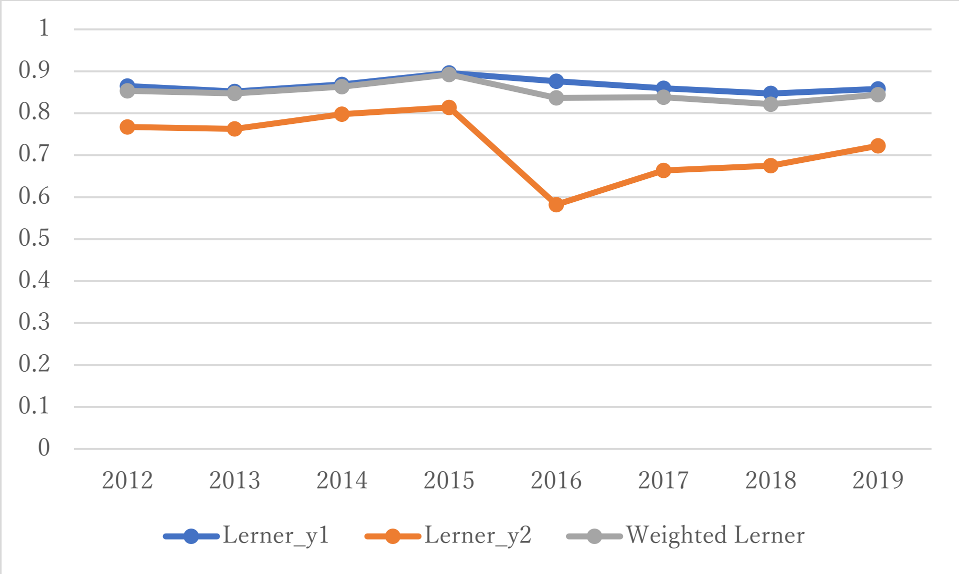
2015					
Target	1112638.5	7616.2	6216.1	660562.3	362069.2
Observed	1142530.9	8211.5	6474.1	660466.6	361127.7
Percentage change	2.69%	7.82%	4.15%	0.015%	0.26%
2016					
Target	1294774	7442.7	6037.5	742655.3	470435.3
Observed	1304970.0	8254.7	6669.4	741818.4	461073.9
Percentage change	0.79%	10.91%	10.47%	0.11%	2.03%
2017					
Target	1347014.36	7298.39	6460.4	826176.8	495082.6
Observed	1374347.9	8329.8	7025.4	825891.5	486414.9
Percentage change	2.03%	14.13%	8.75%	0.035%	1.78%
2018					
Target	1437951.4	7455.3	7189.7	921114.5	515555.8
Observed	1461780.8	8410.0	7629.7	920791.9	508839.0
Percentage change	1.66%	12.81%	6.12%	0.035%	1.32%
2019					
Target	1561634.6	8349.7	7490.3	1034527.7	544136.4
Observed	1582115.0	9860.2	8057.0	1034345.1	537646.5
Percentage change	1.31%	18.09%	7.57%	0.018%	1.21%

In our empirical analysis, we set $\mathbf{g}^x = \left(x_{1o}, x_{2o}\ x_{3o}\right)^{\mathrm{T}} \in \Re^3_{++}$ and $\mathbf{g}^y = \left(y_{1o}, y_{2o}\right)^{\mathrm{T}} \in \Re^2_{++}$ where o represents the evaluated bank o. With these direction vector, $GBS(\mathbf{y}, \mathbf{w}/c)$ in Eq. (14) is units invariant. In the standard directional distance functions, selecting the observed data of the bank under evaluation as the direction is an appropriate one because the value of directional distance functions due to Chambers et al.'s (1996, 1998) parallels the interpretation of radial Shephard (1970) distance functions (Färe et al. 2014) and $GBS(\mathbf{y}, \mathbf{w}/c)$ is an extension of the directional distance function. Since the farthest-distance-based slack inefficiency measure is an extension of the directional distance function, the choice of observation is the natural one. It should be remarked that the current study extends this farthest measure into a closest one in Shephard's indirect cost setting.

The objective function in (14) is based on an extended form of the slack inefficiency measure (Fukuyama and Weber 2009). Although we can theoretically use various direction vectors, the current paper set them as the input and output observations. The use of the observation of the firm under consideration yields the contraction of inputs and the expansion of outputs as a proportion of these production variables.

Figure 1 displays the Lerner indices, consisting of two single-output indices and one multiple-output Lerner index. The results indicate that, overall, the Lerner index calculated using loans as the output is higher than the one using securities as the output. The overall weighted Lerner index is slightly lower than the Lerner index for loans, but the difference between the two is relatively small.

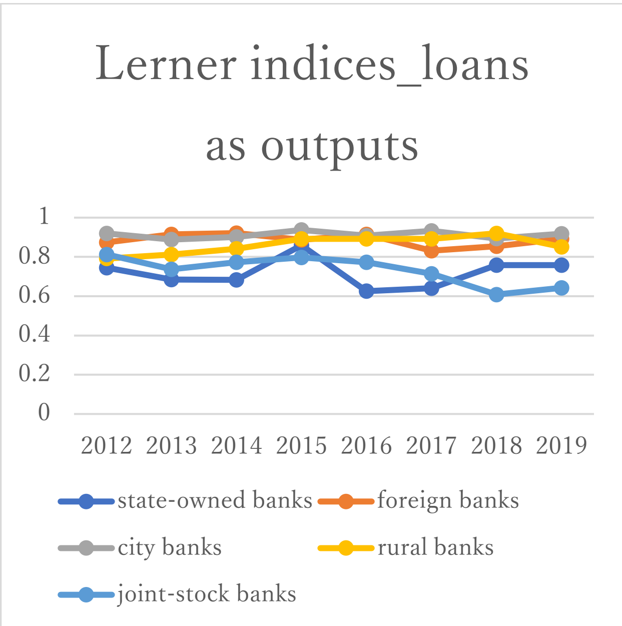
Figure 1 Lerner indices of Chinese commercial banks over 2012-2019

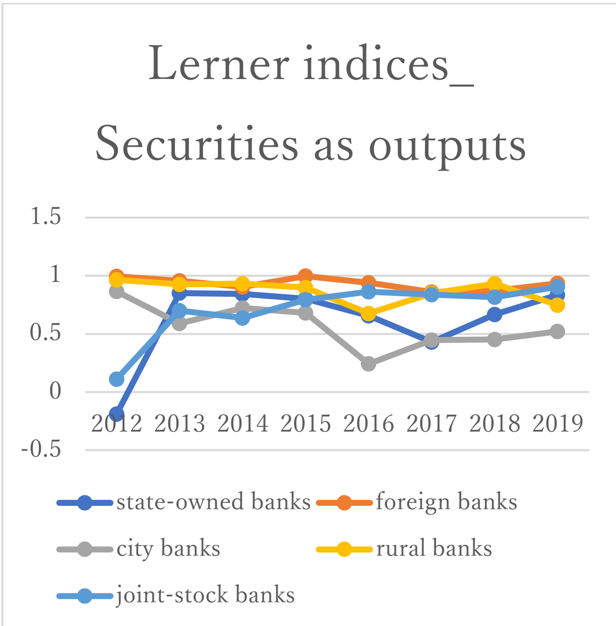


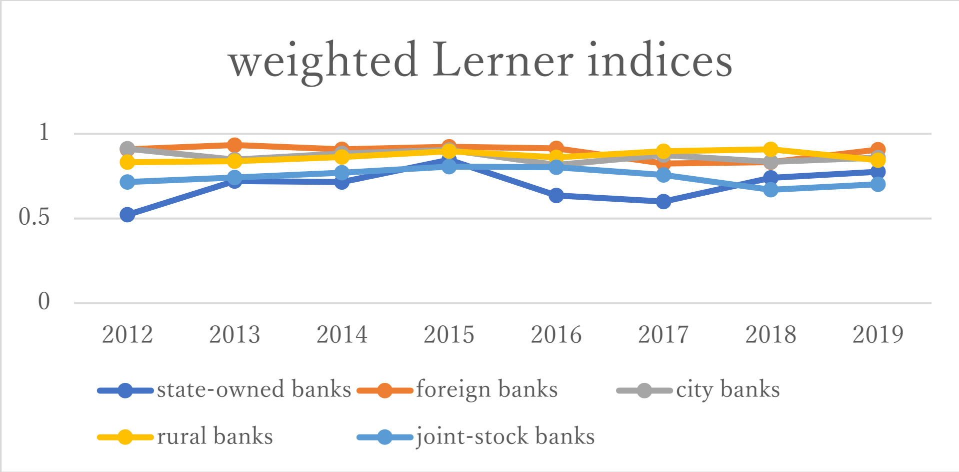
●Lerner_y1 indicates the Lerner indices in loans and Lerner_y2 indicates the Lerner indices in securities.

Figure 2 presents the Lerner indices of different bank ownership types over the examined period. The figure reveals that there is no clear comparison in terms of the level of market power among different bank types in both the loans market and securities market. However, we observe that state-owned and joint-stock banks exhibit greater volatility in terms of market power in the loans market. Similarly, the comparison of market power among different ownership types in the securities market is also unclear, with state-owned banks displaying the highest volatility. In terms of the multiple-output Lerner index, as indicated by the weighted Lerner index, state-owned banks demonstrate the highest volatility.

Figure 2 Lerner indices in Chinese banking over 2011-2018 for different ownership types

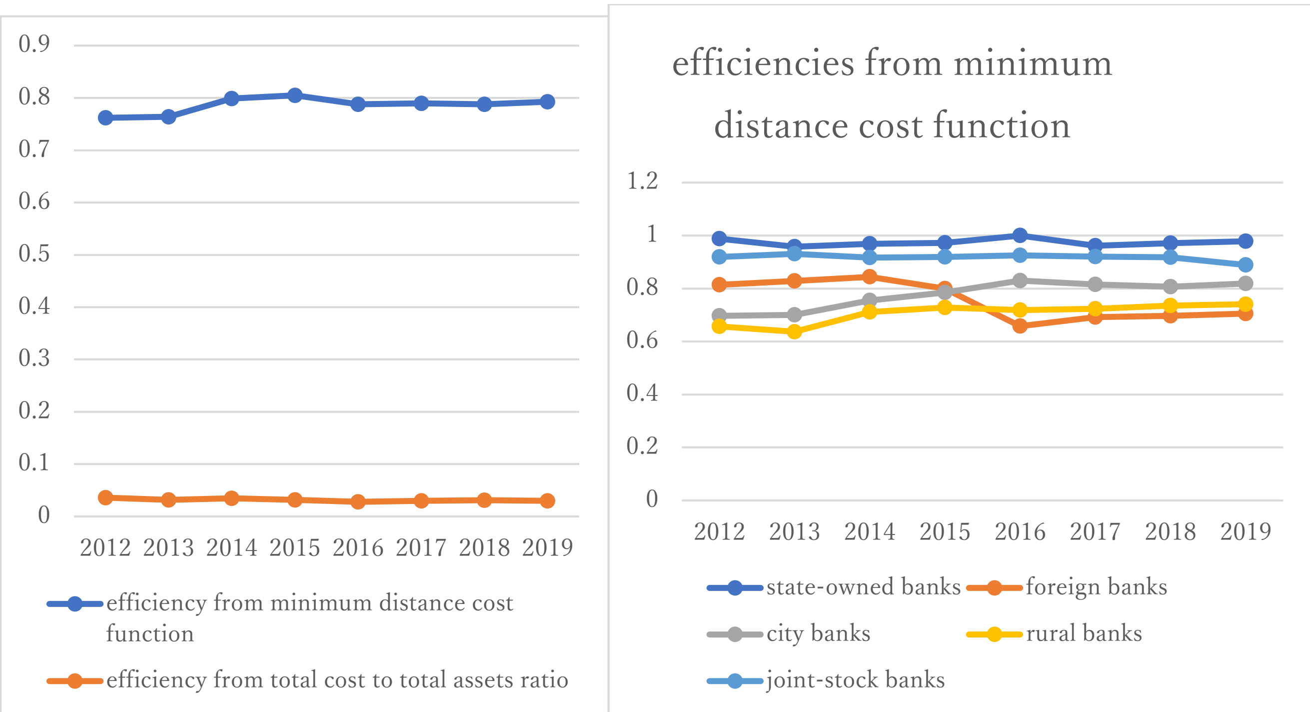


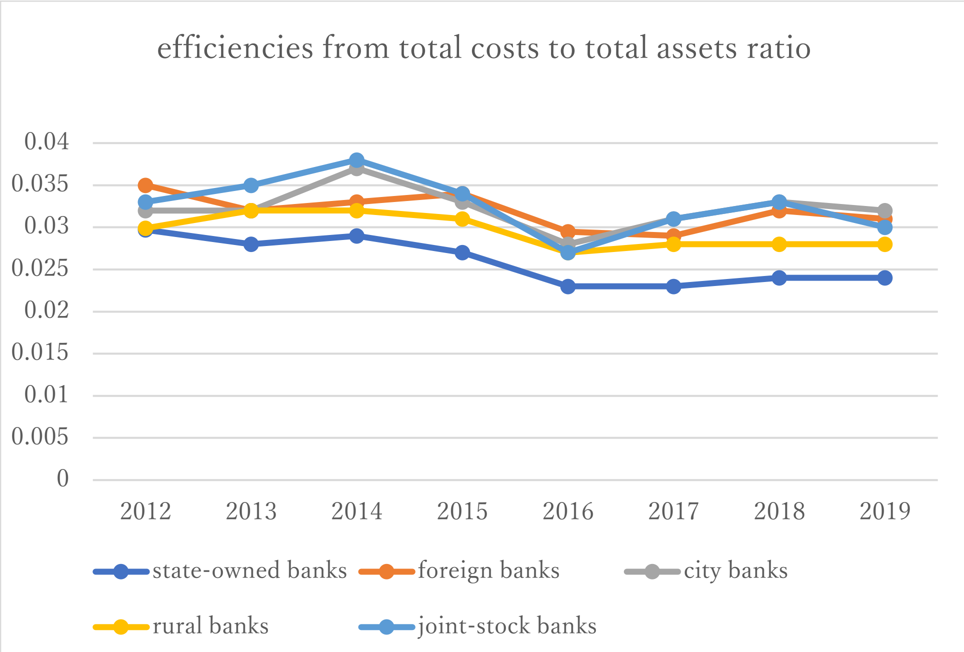




We not only report the results of market power, as reflected by different Lerner indices, but also present the efficiency scores derived from our minimum distance cost function approach. To facilitate comparison, we use a ratio analysis as a proxy for efficiency levels. Specifically, we utilize the ratio of total cost to total assets as an alternative measure of efficiency. Both efficiency measures are presented in Figure 3. The results indicate that efficiency remains relatively stable over the period, although there is some variation between the efficiency levels derived from the minimum distance cost function and the efficiency ratio analysis. We also compare the efficiency levels of different bank types using these two measurements. Based on the efficiency scores generated from the minimum distance cost function approach, the findings suggest that, overall, state-owned banks exhibit the highest level of efficiency, followed by joint-stock banks. For other ownership types, there is no clear comparison due to a certain degree of volatility over the period. The efficiency ratio analysis yields a similar result, highlighting the superior performance of state-owned banks.

Figure 3 Efficiency scores of under minimum distance cost function and ratio analysis





The statistics of the market power determinants are described in Table 4. It shows that the level of market power among Chinese commercial banks does not differ significantly, as reflected by the standard deviation. In terms of bank-specific characteristics, we can see that bank size varies to a greater extent, and the differences in the level of bank capitalization and bank diversification are quite similar, although we observe a smaller difference in securities market share. Chinese banks are found to have the smallest difference in the level of innovation. Finally, the degree of trade openness in China varies across the examined period.

Table 4. Descriptive statistics

Variables	Obs	Mean	Standard deviation	Minimum	Maximum
Bank size	640	5.347	0.824	3.082	7.393
Bank capitalization	640	0.091	0.071	0.039	0.755
Bank innovation	640	0.0013	0.0021	0	0.022
Bank diversification	640	0.081	0.072	0	0.373
Market share in securities	640	0.0125	0.031	3.66e-07	0.217
Trade openness	640	40.9	4.624	35.84	48.27

We test whether the selection of our variables suffers from any issues of multicollinearity. The results are presented in Table 5. The correlation among the independent variables is less than 0.8, indicating that our selection of variables does not exhibit any issues of multicollinearity (Kennedy, 2008).

Table 5. Correlation matrix

	Bank size	Capitalization	Innovation	Diversification	Market share in securities	Trade openness
Bank size	1					

Capitalization	-0.5584	1				
Innovation	-0.1356	0.0038	1			
Diversification	-0.0600	0.3272	-0.0112	1		
Market share in securities	0.6896	-0.1409	-0.0671	0.0539	1	
Trade openness	-0.1451	-0.0444	0.0412	-0.1567	-0.0000	1

Tables 6-8 present the results regarding the impact of bank innovation and trade openness on market power in loans, securities, and overall market power, respectively. The results indicate that the lagged one-period Lerner index is significant, suggesting that market power in the Chinese banking industry exhibits persistence. This finding is supported by Hankir et al. (2011). Regarding the bank-specific determinants, we find that bank size contributes to an improvement in market power in the securities market. However, it has a significant and negative impact on market power in loans. Our findings extend those of Fernandez de Guevara et al. (2005) by explicitly examining the impact of bank size on market power in securities. The positive influence of bank size on market power in the securities market can be explained by various economic mechanisms. Firstly, larger banks have enhanced access to resources such as capital and advanced technology, enabling them to offer a broader range of securities products and services. This advantage helps them attract a larger customer base and establish a more robust brand reputation. Secondly, the utilization of economies of scale allows larger banks to spread their fixed costs over a larger customer base, resulting in lower average costs and potentially higher profits. Additionally, the size and reputation of larger banks can enhance their credibility and trustworthiness within the securities market, attracting a greater number of investors and bolstering their market power.

Conversely, the negative impact of bank size on market power in the loans market can also be attributed to specific economic mechanisms. Firstly, larger banks may encounter difficulties in maintaining personalized customer relationships and offering customized loan products. In contrast, smaller banks may possess a comparative advantage in catering to the specific needs and preferences of borrowers, granting them a competitive edge in the loan market. Secondly, smaller banks often demonstrate greater flexibility and adaptability, allowing them to respond more effectively to dynamic market conditions and provide tailored loan terms to borrowers. These factors contribute to a decrease in market power for larger banks within the loans market. Our findings indicate that large Chinese banks have substantially more experience and higher ability in conducting non-traditional banking businesses. The lower market power in loans for large banks indicates that they have diverted resources from traditional deposit-loan services to various non-traditional activities. It shows that bank capitalization deteriorates market power in loans, but it has a significantly positive impact on market power in securities. Our finding further builds on that of Efthyvoulou and Yildirim (2014) by examining the impact of bank capitalization on market power in securities. Our results indicate that higher-capitalized banks have a higher ability to engage in the provision of non-traditional businesses. Although these types of activities come with a higher level of risk to a certain extent due to the lack of knowledge and expertise, banks with higher levels of capitalization would be able to absorb potential negative shocks. In comparison, banks with lower capitalization will divert resources to traditional loan services.

Bank innovation is found to have a significant and positive impact on market power in securities, which aligns with our hypothesis 2. However, the negative impact of bank innovation on market power in loans contradicts our hypothesis 1. We explain the positive impact by the fact that innovation often brings about cost reduction (Bos et al., 2013). Additionally, bank innovation has the potential to introduce new types of non-traditional banking products, which can increase income while reducing costs, thereby boosting market power in securities. On the other hand, the allocation of efforts and resources towards innovation in non-traditional banking businesses can diminish the income derived from traditional loan services. Furthermore, the lack of resources may increase the additional cost of producing additional units of loans, resulting in a reduction in market power in loans. The results demonstrate that bank innovation does not significantly impact the overall bank market power, which contradicts our hypothesis 3. This finding reflects the balancing effect between the positive impact on market power in securities and the negative impact on market power in loans. This balancing effect can be explained by economic mechanisms such as the trade-off between the two financial segments. Bank innovation may lead to a reallocation of resources and strategic focus, where the positive impact in securities is counteracted by the negative impact in loans.

We further find that bank diversification significantly affects market power in loans in a negative manner but significantly affects market power in securities in a positive manner. We extend the study of Bolt and Humphrey (2010) by explicitly investigating the impact of bank diversification on market power in securities. Valverde and Fernandez (2007) argue that non-interest income, as reflected by diversification, is negatively related to net interest margin. Additionally, Shaban et al. (2014) argue that the idiosyncratic risk stemming from diversification can lead to complacency in bank managers' monitoring, resulting in increased costs for banks. Higher levels of diversification, indicated by larger volumes of non-interest income, imply that banks are proficient in offering various non-traditional banking products. It also suggests that a certain level of economies of scale and scope has been achieved through the provision of different types of non-traditional banking products. This, in turn, leads to an improvement in market power in securities.

Market share in securities is found to be a contributor to market power in the loans market, but it has a significantly negative impact on market power in securities. We initially intended to include market share in loans as one of the independent variables because loans are an important banking asset. However, due to the issue of multicollinearity between market share in securities and market share in loans, we had to drop the variable from the list. Therefore, we can interpret our results as higher market shares in loans leading to higher market power in loans, which is in accordance with the relative market power hypothesis (Garza-Garcia, 2012). The negative impact of market share in securities on market power in securities can be interpreted as Chinese banks engaging in large volumes of non-traditional banking businesses, earning smaller margins due to a lack of knowledge, skills, and expertise in these businesses. Furthermore, we find that trade openness decreases market power in loans, aligning with Kim's (2000) findings in manufacturing industries in Korea and supporting our hypothesis 4. The significant and positive impact of trade openness on market power in securities is in line with our hypothesis 5. Regarding the overall level of market power, our results show that trade openness has a significant and negative impact, indicating that the negative effect of trade openness on market power in loans is stronger than the positive impact on market power in securities.

Table 6. The impact of innovation and trade openness on bank market power (Loans as outputs)

	Coefficient	Standard error	Z	P>|z|	95% confidence interval	
Endogenous variables						
Market share in securities	1.564	0.055	28.7	0.000	1.458	1.671
Bank size	-0.126	0.005	-26.42	0.000	-0.136	-0.117
Exogenous variables						
Lag of dependent variable	0.218	0.005	-42.47	0.000	-0.228	-0.208
Bank innovation	-1.707	0.625	-2.73	0.006	-2.932	-0.482
Bank diversification	-0.403	0.032	-12.47	0.000	-0.467	-0.34
Bank capitalization	-1.167	0.088	-13.19	0.000	-1.34	-0.993
Trade openness	-0.014	0.0002	-57.91	0.000	-0.015	-0.014
Year effect	-0.0099	0.0008	-12.18	0.000	-0.011	-0.008
Constant	3.355	0.073	46.27	0.000	3.213	3.497
Number of observations	560					
Number of instruments	90					
Wald chi2			6557.73	0.000		
AR(1)			-4.5231	0.000		
AR(2)			-1.2826	0.1996		
Sargan test			75.53	0.6507		

Table 7. The impact of innovation and trade openness on bank market power (securities as outputs)

	Coefficient	Standard error	Z	P>|z|	95% confidence interval	
Endogenous variables						
Market share in securities	-1.477	0.083	-17.82	0.000	-1.64	-1.315
Bank size	0.091	0.003	36.08	0.000	0.086	0.096
Exogenous variables						

Lag of dependent variable	-0.047	0.001	-49.54	0.000	-0.049	-0.045
Bank innovation	13.25	2.872	4.61	0.000	7.623	18.88
Bank diversification	1.762	0.069	25.36	0.000	1.626	1.898
Bank capitalization	2.093	0.059	35.20	0.000	1.977	2.21
Trade openness	0.021	0.0007	28.64	0.000	0.0198	0.023
Year effect	-0.0096	0.0007	-13.45	0.000	-0.011	-0.008
Constant	-1.51	0.059	-25.29	0.000	-1.626	-1.395
Number of observations	560					
Number of instruments	90					
Wald chi2			21524.86	0.000		
AR(1)			-3.6663	0.0002		
AR(2)			0.528	0.597		
Sargan test			77.708	0.5830		

Table 8. The impact of innovation and trade openness on bank market power (loans and securities as outputs)

	Coefficient	Standard error	Z	P>|z|	95% confidence interval	
Endogenous variables						
Market share in securities	-0.169	0.043	-3.89	0.000	-0.255	-0.084
Bank size	-0.003	0.003	-1.00	0.317	-0.008	0.003
Exogenous variables						
Lag of dependent variable	-0.23	0.005	-44.66	0.000	-0.241	-0.22
Bank innovation	-2.311	1.731	-1.34	0.182	-5.703	1.081
Bank diversification	-0.217	0.026	-8.25	0.000	-0.269	-0.165
Bank capitalization	-0.29	0.063	-4.60	0.000	-0.414	-0.166
Trade openness	-0.007	0.0004	-18.84	0.000	-0.008	-0.006
Year effect	-0.019	0.0003	-71.3	0.000	-0.019	-0.018
Constant	1.508	0.047	32.31	0.000	1.416	1.599
Number of observations	560					
Number of instruments	90					
Wald chi2			36880.62	0.000		

AR(1)			-4.7329	0.0002		
AR(2)			-1.2171	0.2236		
Sargan test			77.081	0.6027		

An important issue here is whether this regression can be given a causal interpretation. Uncovering causal structures is a key problem in many scientific fields. It is well known that controlled randomized experiments are ideal for inferring causal relations; in most cases, however, we have observational data which do not satisfy the randomization principles (Pearl 2009; Peters et al., 2013; Imbens and Rubin 2015; Peters et al., 2017). Granger causality is a powerful tool for detecting predictability in time-series but predictability is not the same as causality. While least-squares regressions contain all predictors, utilizing simply the causal predictors results in models that are invariant for all observations across multiple 'environments' or 'heterogeneity patterns' (Pfister et al., 2019). Without having such knowledge environments and/or heterogeneity patterns, it is possible to infer causal predictions from time-ordered data. In this data-based causality analysis, we exploit Bayesian causal inference which has a long history and many contributions.

Along this line of research, we start with the recent paper by Wang and Blei (2019) and present their deconfounder approach to causal inference using the example in which movie revenues depend, among other things, on casting. The data set contains values on revenues and a given casting for each movie. The question is what revenues are probable, in the light of this data, had an alternative casting been used instead. Suppose we partition the data into a set that we use, say $\mathcal{X} = \{x_i^{obs}\}_{i=1}^{n_1}$ and a hold-out sample $\{x_i^{held}\}_{i=1}^{n_o}$. Based on these samples, we can compute not only the posterior $p(z_i|\mathcal{X})$ but also the distribution $p(x_i^{held}|z_i)$. The posterior predictive distribution has density:

$$p(x_i^{held}|x_i^{obs}) = \int p\,(x_i^{held}|z_i)p(z_i|x_i^{obs})\,\mathrm{d}z_i. \tag{20}$$

To compute fitted and actual data, Wang and Blei (2019) suggest using

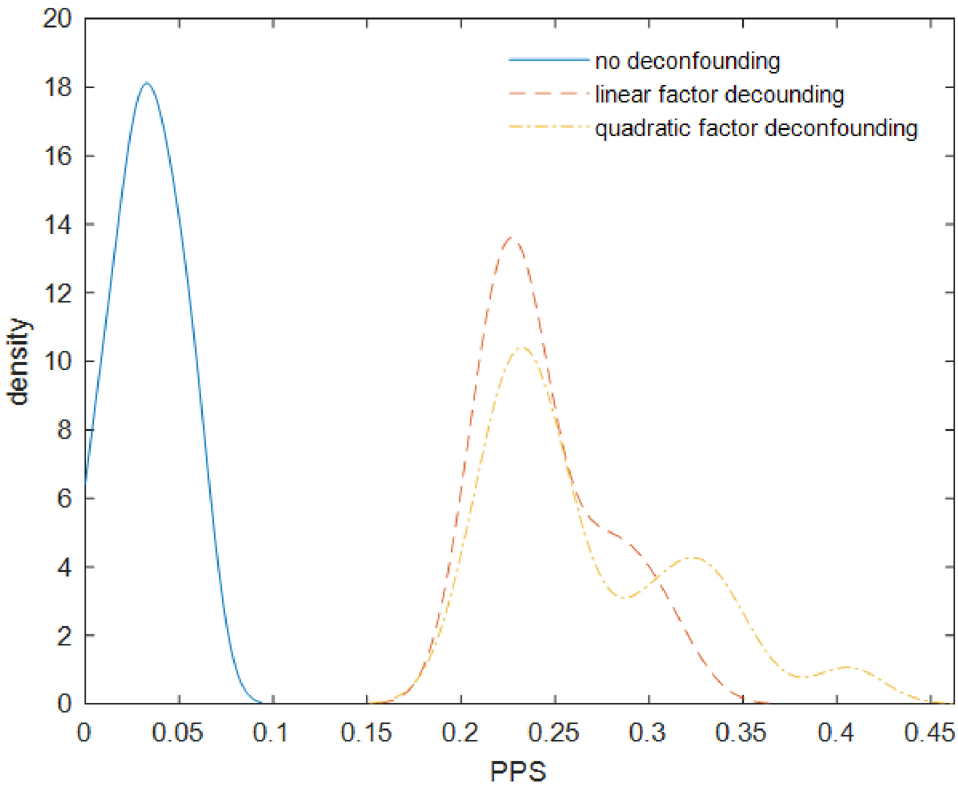
$$\tau(x_i^{held}) = \mathbb{E}_z\big[\log\, p\,(x_i^{held}|z)|x_i^{obs}\big]. \tag{21}$$

If $\hat{x}_i^{held}$ is a draw from the distribution whose density is Eq. (20) then the posterior predictive score (PPS) is:

$$PPS = \Pr\big(\tau(x_i^{held}) < \tau(x_i^{held})\big). \tag{22}$$

This probability can be evaluated using the Monte Carlo method. We first generate any factors and test whether the present model can be given a structural (causal) interpretation. Using 10,000 replications our results for the Wang and Blei (2019) posterior predictive p-value (PPS) are reported in Figure 4. Roughly, posterior predictive p-values in excess of 0.10 support causal interpretation according to Wang and Blei (2019). In our case, even the original model passes their test, so it can be given a causal interpretation which solidifies our conclusions. PPS is based on extracting factors by doing factor analysis as we describe in the text. We look whether after deconfounding PPS > .10.

Figure 4 Wang and Blei (2019) posterior predictive score (10,000 replications)



5. Additional analysis

We also conducted additional analysis to examine the impact of bank innovation and trade openness on market power in loans, securities, and the overall level of market power for different ownership types. The results are presented in Tables 9-11. Regarding bank innovation, the findings suggest that state-owned banks and rural banks with higher levels of innovation exhibit higher market power in loans, while joint-stock commercial banks with higher levels of innovation show lower market power in loans. In the securities market, the results suggest that state-owned banks with higher innovation have lower market power, while joint-stock banks with higher innovation demonstrate higher market power. For the overall level of market power, our results indicate that state-owned and joint-stock banks with higher innovation have higher market power, while foreign banks with higher innovation have lower market power. These results imply that the positive impact of innovation on market power in loans is stronger for state-owned banks than the negative impact of innovation on securities. Conversely, for joint-stock commercial banks, the positive impact of innovation on market power in securities is stronger than the negative impact of innovation on market power in loans. Regarding the impact of trade openness for different ownership types, our results indicate that trade openness has a significant and negative impact on market power in loans, a significant and positive impact on market power in securities, and a significant and negative impact on the overall level of market power across different ownership types. This suggests that the negative impact of trade openness on market power in loans is stronger for different ownership types compared to the positive impact on market power in securities.

Table 9 The impact of innovation and trade openness on bank market power for different ownerships (loans as the outputs)

	Coefficient	Standard error	Z	P>|z|	95% confidence interval	
Endogenous variables						
Bank size	-0.073	0.005	-14.24	0.000	-0.083	-0.063
Market share in securities	4.126	0.332	12.43	0.000	3.475	4.776
Exogenous variables						
Lag of dependent variable	-0.251	0.019	-13.24	0.000	-0.288	-0.214
Bank capitalization	-0.397	0.083	-4.77	0.000	-0.56	-0.234
Bank diversification	-0.277	0.051	-5.43	0.000	-0.376	-0.177
State*innovation	346.26	45.72	7.57	0.000	256.66	435.86
Joint-stock*innovation	-43.807	14.791	-2.96	0.003	-72.796	-14.818
Foreign*innovation	14.086	17.855	0.79	0.430	-20.91	49.082
City*innovation	-0.66	0.867	-0.76	0.446	-2.359	1.038
Rural*innovation	46.544	17.987	2.59	0.010	11.288	81.799
State*open trade	-0.034	0.0008	-44.24	0.000	-0.036	-0.033
Foreign*open trade	-0.012	0.001	-12.43	0.000	-0.014	-0.01
Joint-stock*open trade	-0.017	0.001	-16.36	0.000	-0.019	-0.015
City*open trade	-0.008	0.001	-8.68	0.000	-0.01	-0.006
Rural*open trade	-0.012	0.001	-9.95	0.000	-0.014	-0.009
Year effect	-0.011	0.002	-6.22	0.000	-0.015	-0.008
Constant	2.508	0.097	25.88	0.000	2.318	2.698
Number of observations	560					
Number of instruments	98					
Wald chi2			5444.18	0.000		
AR(1)			-4.1771	0.000		
AR(2)			-1.1844	0.2363		
Sargan test			72.571	0.7369		

Table 10 The impact of innovation and trade openness on bank market power for different ownerships (securities as the outputs)

	Coefficient	Standard error	Z	P>|z|	95% confidence interval

Endogenous variables						
Bank size	-0.029	0.011	-2.59	0.010	-0.05	-0.007
Market share in securities	1.13	0.407	2.78	0.006	0.332	1.928
Exogenous variables						
Lag of dependent variable	0.138	0.005	30.56	0.000	0.129	0.147
Bank capitalization	0.73	0.151	4.81	0.000	0.433	1.028
Bank diversification	1.202	0.164	7.35	0.000	0.882	1.523
State*innovation	-876.58	119.66	-7.33	0.000	-1111.11	-642.05
Joint-stock*innovation	110.396	47.43	2.33	0.020	17.43	203.36
Foreign*innovation	-60.25	32.2	-1.87	0.061	-123.37	2.863
City*innovation	14.74	9.161	1.61	0.108	-3.215	32.694
Rural*innovation	-18.4	73.575	-0.25	0.803	-162.61	125.8
State*open trade	0.045	0.003	17.22	0.000	0.04	0.05
Foreign*open trade	0.023	0.002	12.81	0.000	0.019	0.026
Joint-stock*open trade	0.017	0.002	10.23	0.000	0.014	0.021
City*open trade	0.019	0.002	11.56	0.000	0.015	0.022
Rural*open trade	0.033	0.003	11.33	0.000	0.027	0.038
Year effect	0.02	0.003	5.80	0.000	0.013	0.027
Constant	-0.371	0.189	-1.96	0.050	-0.741	-0.0006
Number of observations	559					
Number of instruments	98					
Wald chi2			262450.58	0.000		
AR(1)			-3.8071	0.0001		
AR(2)			0.2118	0.8323		
Sargan test			62.48387	0.9261		

Table 11 The impact of innovation and trade openness on bank market power for different ownerships (loans and securities as the outputs)

	Coefficient	Standard error	Z	P>|z|	95% confidence interval	
Endogenous variables						
Bank size	0.003	0.006	0.45	0.655	-0.0096	0.015
Market share in securities	4.911	0.144	34.10	0.000	4.628	5.193

Exogenous variables						
Lag of dependent variable	-0.248	0.01	-24.48	0.000	-0.268	-0.228
Bank capitalization	-0.06	0.091	-0.66	0.512	-0.239	0.119
Bank diversification	-0.155	0.043	-3.65	0.000	-0.239	-0.072
State*innovation	258.09	19.944	12.94	0.000	219.002	297.18
Joint-stock*innovation	26.039	12.172	2.14	0.032	2.182	49.896
Foreign*innovation	-72.203	16.549	-4.36	0.000	-104.64	-39.77
City*innovation	1.014	1.456	0.70	0.486	-1.84	3.867
Rural*innovation	23.313	17.525	1.33	0.183	-11.036	57.663
State*open trade	-0.033	0.001	-34.30	0.000	-0.035	-0.031
Foreign*open trade	-0.004	0.0008	-5.16	0.000	-0.006	-0.003
Joint-stock*open trade	-0.015	0.0008	-17.50	0.000	-0.016	-0.013
City*open trade	-0.007	0.0008	-7.83	0.000	-0.008	-0.005
Rural*open trade	-0.006	0.001	-6.07	0.000	-0.0077	-0.004
Year effect	-0.021	0.001	-20.94	0.000	-0.023	-0.019
Constant	1.416	0.104	13.68	0.000	1.213	1.619
Number of observations	560					
Number of instruments	98					
Wald chi2			29432.86	0.000		
AR(1)			-4.7208	0.000		
AR(2)			-1.4331	0.1518		
Sargan test			71.65	0.7615		

6. Policy implications

The results have important implications for policy-making purposes: 1)In addition to efficiency improvement, it is crucial to prioritize the stability of efficiency over the examined period; 2)Policies related to innovation should be carefully considered and coordinated, taking into account its negative impact on market power in loans, positive impact on market power in securities, and the overall negative impact on the overall level of market power; 3) The degree of trade openness should be encouraged but also well controlled due to its negative impact on market power in loans and the overall level of market power, despite the market power enhancement it brings in the securities market; 4)Special attention should be given to innovation by state-owned commercial banks and joint-stock commercial banks.

7. Concluding remarks

This paper aims to investigate the determinants of market power in the banking sector, focusing on the influence of trade openness and innovation. Additionally, we propose an innovative method to measure bank competition. Specifically, we have developed a procedure for estimating a multi-output Lerner index using nonparametric DEA, employing a minimum distance cost function approach. This approach addresses the issue of zero-value multipliers and provides efficiency score estimates alongside the Lerner index. Our results indicate that the Lerner index is highest for loans, followed by the overall weighted Lerner index, while the Lerner index for securities is the lowest. Fixed assets are identified as a factor of production that Chinese bank managers should prioritize, in comparison to deposits and labor. However, a clear comparison of market power levels across different bank ownership types in loans, securities, and the overall market power is not available in our study. In our second-stage analysis, we find that bank innovation and trade openness have a significant and negative impact on market power in loans, but a significant and positive impact on market power in securities. Concerning the overall market power level, bank innovation does not show a significant impact, while trade openness has a significantly negative impact. We observe that higher levels of innovation among state-owned commercial banks and joint-stock commercial banks improve the overall market power. Furthermore, across all bank ownership types, trade openness has a significant and negative impact on market power in loans but a significant and positive impact on market power in securities. The impact on the overall market power level is significant and negative.

However, it is important to acknowledge several limitations in our study. Firstly, for the second output variable (securities), we should have considered interest income from holding securities when calculating output prices and the related Lerner index. However, relevant data regarding expenses and interest income from holding securities was not available. Secondly, non-interest income should have included off-balance sheet activities when considering non-interest income. Unfortunately, due to data availability issues, these factors were not incorporated in the current study. Lastly, the study did not consider the potential impact of Fintech companies, which could be a determinant of banks' market power in China, given technological developments in the financial sector. Based on these limitations, we recommend that future studies: 1) collect more data on interest income and expenses related to holding securities to include them in the calculation of output prices and the Lerner index; 2) gather additional data on off-balance sheet items to incorporate them in the calculation of output prices and the Lerner index; and 3) collect data on the size and number of Fintech companies in China to investigate their impact on bank market power.

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