Impact of Macroprudential Policies on Chinese Banking Competition

Abstract

This study employs a dual-data approach, leveraging both bank and city-level datasets, to investigate the collateral consequences of macroprudential regulations, with a specific emphasis on non-regulatory determinants. Our analysis uncovers that such policies inadvertently undermine banking competitiveness, as evidenced by a reduction in banks' asset growth coupled with an augmentation in their income growth. Employing a difference-in-differences methodology, we capitalize on the exogenous stimulus provided by the enhancement of macroprudential policies in China. Our findings indicate that larger banks are more significantly impacted by these policies, leading to an elevated Lerner Index.

Keywords: Macroprudential Policies, Banking Competition Dynamics, Regulatory Frameworks, Financial Stability

JEL: E58, E63, G21, G28

1. Introduction

Over recent decades, macroprudential policies have emerged as a critical tool in economic governance. Numerous studies have underscored the direct effects of these policies on banking operations. Notably, an array of international research demonstrates that implementing macroprudential measures plays a vital role in curbing pro-cyclical credit expansions, moderating housing price surges, and reducing systemic financial risks, as evidenced by studies from Lim et al. (2011), Claessens et al. (2013), Cerutti et al. (2017), Akinci and Olmstead-Rumsey (2018), and Nakatani (2020). While the global trajectory of macroprudential policy has been well-documented, China offers an intriguing context due to its brisk economic expansion and the ongoing evolution of its financial regulatory landscape.

In 2010, China embraced a "countercyclical financial macroprudential management framework." This approach evolved with the introduction of the Macro Prudential Assessment (MPA) system in 2016. Further institutional developments occurred with the establishment of the Central Committee's Office for Financial and Economic Affairs in February 2019. Marking a recent milestone in 2021, China released a significant policy document, the "Guidelines for Macroprudential Policy (Trial)," setting a new course for its macroprudential policy framework.

The Chinese case presents a compelling context for examining banking competition, as it is shaped by distinct characteristics that may lead to unintended outcomes of macroeconomic policies. In China, the banking sector is foundational, holding over 90% of the nation's financial assets. This vast pool of assets is distributed among more than 1,800 banks, with a relatively dispersed concentration. Data from the National Financial Regulatory Administration indicates a varied distribution of assets: 41.7% by large commercial banks, 17% by joint-stock commercial banks, 13.7% by city commercial banks, and 13.6% by rural commercial banks.

Despite the high number of banks, which typically suggests intense competition, China's banking landscape is characterized by significant regulatory oversight and prevalent government ownership. Interest rates are often capped, either explicitly or implicitly, facilitating the provision of low-cost loans to favored large enterprises and

government entities. The varying degrees of state ownership among banks result in disparate levels of implicit guarantees and competitive capabilities. Mirzaei et al. (2021) noted that state ownership could impair the effectiveness of macroprudential policies.

Furthermore, a majority of commercial banks in China are either city or rural commercial banks. These banks operate within legally defined areas, limiting their competitive scope but simultaneously granting them a degree of monopolistic power within their designated regions. Given these multifaceted factors, the extent to which macroprudential policies impact banking competition in China is challenging to determine solely from a theoretical standpoint, making it predominantly an empirical question.

In this study, we explore the influence of macroprudential policies on the competitive dynamics within the Chinese banking sector. Our findings indicate that these policies have markedly reduced competition among banks in China. The Lerner Index, a key indicator of competitive status, serves as our primary analytical tool. Through our channel analysis, we observe that macroprudential policies potentially enhance the marginal output of banks. This enhancement appears to be driven by a deceleration in asset growth coupled with an escalation in revenue growth, aligning with the objectives of China's macroprudential policies.

To further validate our findings, we employ exogenous shocks and the Generalized Difference-in-Differences (DID) Model, which reveal that larger banks are more likely to benefit from macroprudential policies. For a robustness check, we incorporate the Herfindahl-Hirschman Index (HHI) and city-level data, providing an alternative perspective to support our hypothesis.

The structure of this paper is as follows: Section 2 provides a comprehensive review of the relevant literature and formulates the hypotheses. Section 3 describes the data sources and outlines the methodological approach, detailing the models employed. Section 4 presents the main empirical results of the study. Section 5 engages in a series of robustness tests to validate the findings. Finally, Section 6 concludes the research.

2. Literature Review and Hypothesis Development

2.1 Literature Review

To date, there is a limited but growing body of research that directly addresses the interplay between macroprudential policies and banking competition. González (2022)

conducted a comprehensive analysis using data from 2,511 banks across 52 countries. This study utilized the bank-specific Lerner index as a metric for assessing banking competition. By applying a Difference-in-Differences approach, González discerned a notable trend: macroprudential policies typically enhance bank competition, thereby bolstering banking stability.

In another significant contribution, Mirzaei and Moore (2021) assembled data from banks in 58 countries to create a country-specific panel dataset. They applied the Lerner index for competitiveness evaluation. Their methodology, which included the use of dynamic panel data and the System Generalized Method of Moments (GMM), indicated that macroprudential policies generally have a constricting effect on banking competition.

Additionally, Scalco et al. (2021) focused on the Brazilian banking sector, using stochastic frontier analysis to examine the market's monopolistic characteristics. Their study highlighted a reduction in competitive dynamics within Brazil's banking industry, a change they attributed to the influence of macroprudential policies.

The existing literature on the relationship between macroprudential policies and banking competition is confronted with two significant challenges. Firstly, cross-country analyses often grapple with the issue of inconsistent measures, leading to potential measurement errors and estimation biases, as highlighted by Du et al. (2022). This inconsistency is evident in the divergent conclusions drawn by different cross-country studies. Secondly, while existing studies propose various mechanisms through which macroprudential policies might affect banking competition, they often lack concrete empirical evidence to substantiate these theories.

Our study addresses these gaps in the current body of research. By narrowing our focus to a single country, we are able to utilize consistent measures of banking competition, thereby ensuring comparability in the assessment of competitive power. Furthermore, our research sheds light on the unique mechanisms at play in the context of China's banking sector, examining how macroprudential policies may influence competition, and underpins these insights with solid empirical evidence. The robustness of our findings is bolstered by the extensive sample of banks under consideration and

the frequent adjustments in macroprudential policies, providing a strong foundation for our empirical analysis.

2.2 Hypothesis Development

Since 2011, China's macroprudential policy framework, orchestrated by the People's Bank of China (PBOC), has predominantly focused on the banking sector. Initially, the PBOC employed a dynamic reserve requirement, tailored to individual banks' operations and PBOC's assessment of the macroeconomic climate. This approach evolved in 2016 into a more comprehensive system, the Macro Prudential Assessment (MPA), which introduced a suite of tools. It wasn't until 2021 that a detailed official document, the Guidelines for Macroprudential Policy (Trial), was issued, elucidating the objectives of these policies: primarily to avert systemic financial risks, including the cyclical accumulation of risk and risk contagion.

This paper concentrates on key macroprudential tools relevant to banking competition. The foremost among these is the macroprudential capital requirement, a dynamic, bank-specific minimum capital mandate. Its determinants include a macroeconomic parameter set by the PBOC, the banks' broad credit growth, and legal capital requirements. The macroeconomic parameter influences all banks, with a higher parameter leading to increased capital requirements. Broad credit growth encompasses various asset classes, and rapid asset expansion triggers higher capital demands, potentially curtailing banks' asset growth. Particularly, larger or more systemically important banks face lower credit growth quotas.

Real estate macroprudential policies, utilizing tools like Loan-to-Value (LTV) ratios, also impact banking operations. As housing credit forms a substantial portion of China's credit landscape, LTV restrictions can limit banks' asset growth.

Liquidity risk management is another key area, with instruments like liquidity coverage ratios and net stable funding ratios ensuring banks maintain sufficient liquid assets. Such measures not only bolster financial system stability but also, as Chen et al. (2021) note, can enhance banks' profitability by mitigating liquidity risk.

Credit quality oversight, through non-performing loan ratios and provision coverage ratios, mandates rigorous loan screening and shock preparedness, potentially boosting bank profitability.

Finally, Systemically Important Financial Institutions (SIFIs) are subject to

heightened regulatory scrutiny, including increased capital and asset quality requirements, to reduce contagion risk. These measures typically result in slower asset growth and enhanced operational soundness for SIFIs.

Based on the impacts of these macroprudential tools, we propose two hypotheses:

Hypothesis 1: The tightening of macroprudential policy in China tends to reduce banking competition, thereby augmenting banks' monopoly power.

Hypothesis 2: Banks subjected to more stringent macroprudential requirements are likely to exhibit greater monopoly power, as evidenced by their operational and financial metrics.

3. Data and Empirical Models

Our dataset is derived from the Chinese Research Data Services Platform (CNRDS)[1], supplemented by data from BankFocus for in-depth robustness checks. Information pertaining to macroprudential policies is sourced from the International Monetary Fund's iMaPP database. Additionally, macroeconomic time-series data is collated from two key sources: the Wind database and the China Stock Market and Accounting Research Database (CSMAR)[2].

To ensure the accuracy and reliability of our data, and to mitigate the effects of statistical anomalies, we have employed a 5% winsorization process on both the bank-level financial data and the macroeconomic time-series data. This statistical technique is crucial for limiting the influence of extreme values in our dataset.

The bank-level panel data, which form the backbone of our analysis, are comprehensively detailed in Table 1, providing a clear view of the descriptive statistics that underpin our study.

[Insert Table 1]

This study sources its macroprudential policy data from the IMF's iMaPP database, as employed in Alam et al. (2019). This comprehensive database features monthly updates on macroprudential policies from over 134 countries worldwide. It categorizes

1 For more comprehensive information, please visit their official website: https://www.cnrds.com/Home/Login.

2 For more comprehensive information, please visit their official websites. For WIND, https://www.wind.com.cn/portal/en/AboutUs/index.html;
For CSMAR, https://www.gtadata.com/csmar.html?v=#/index.

each policy into one of 17 distinct classes, providing standardized descriptions applicable to each country. We specifically extract the time series data of macroprudential policies implemented in China, capturing all tools used in the Chinese context within these 17 policy categories.

To evaluate the direction of each macroprudential policy (whether it is being tightened, loosened, or remains unchanged), the iMaPP database utilizes a narrative approach. Each policy change is assigned a value: +1 for tightening, -1 for loosening, and 0 for no change. By summing the values from these 17 policy categories on a monthly basis, we derive an overarching Macroprudential Policy Index (MPI), which reflects the comprehensive stance of macroprudential policy for each month. This monthly MPI is then aggregated annually to synchronize with the frequency of our bank panel data.

Our research also incorporates the use of the Lerner index, a bank-specific metric for assessing competition. The computation of the Lerner index involves various methodologies, as discussed by Shaffer and Spierdijk (2020) and Spierdijk and Zaouras (2018). In this study, we predominantly adhere to the computation approach outlined by Anginer et al. (2014), ensuring a consistent and reliable measure of banking competition across our dataset.

In our analysis, we define the Lerner Index as per Equation (1):

$$Lerner_{i,t} = \frac{P_{i,t} - MC_{i,t}}{P_{i,t}} \tag{1}$$

where $P_{i,t}$ represents the marginal revenue of bank *i* in year *t*, calculated as the ratio of total revenue to total assets. $MC_{i,t}$ denotes the marginal cost for the same bank and year. Marginal costs are typically unobservable in raw data and are estimated from banking fiscal data via a cost function, often in a transcendental logarithmic form. We estimate this cost function using constrained pooled ordinary least squares (Pooled OLS) on the combined panel data. This estimation process aids in determining the first derivative, which, when applied to total assets, yields the marginal cost.

The logarithmic cost function is expressed as follows:

$$lnC_{i,t} = \beta_0 + \beta_A lnA_{i,t} + \frac{1}{2}\beta_{AA}\left(lnA_{i,t}\right)^2 + \sum_{k=1}^{3}\beta_k lnw_{k,i,t} + \frac{1}{2}\sum_{k=1}^{3}\sum_{m=1}^{3}\beta_{km} lnw_{k,i,t} lnw_{m,i,t} + \sum_{k=1}^{3}\beta_{kA} lnA_{i,t} lnw_{k,i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

where $C_{i,t}$ is the total cost for bank *i* in year *t*, including interest and various non-interest expenses. $A_{i,t}$ indicates the total output of bank *i* in year *t*, with total assets serving as a proxy. $w_{k,i,t}$ signifies input prices for capital (*k* = 1), labor (*k* = 2), and funds (*k* = 3). The capital price is the ratio of non-interest expense minus personnel expenses to total assets, labor price is personnel expenses to total assets, and fund price is interest expenses to total assets. μ_i and δ_t are bank and year dummies, respectively, and $\varepsilon_{i,t}$ is the random error term. The variables are in natural logarithms, and the regression is estimated via pooled OLS. Constraints are applied for homogeneity:

$$\sum_{k=1}^{3}\beta_k = 1; \sum_{k=1}^{3}\beta_{km} = 0 \ \forall m; \sum_{k=1}^{3}\beta_{kA} = 0 \quad (3)$$

The marginal cost $MC_{i,t}$ for bank *i* in year *t* is derived from the parameters estimated in equation (2):

$$MC_{i,t} = \frac{\partial C_{i,t}}{\partial A_{i,t}} = \frac{C_{i,t}}{A_{i,t}} \times \left(\beta_A + \beta_{AA} lnA_{i,t} + \sum_{k}^{3}\beta_{kA} lnw_{k,i,t}\right) \quad (4)$$

Our bank-level analysis includes specific control variables for each bank, as well as broader macroeconomic and financial variables. Bank-specific controls encompass capital adequacy ratio, non-interest income, net interest margin, non-performing loan ratio, provision coverage ratio, total asset size, and the loan-to-deposit ratio. Macroeconomic and financial controls include real GDP growth rate, M2 growth rate, and CPI growth rate. Table 2 provides detailed information on these variables, including names, symbols, definitions, and data sources.

[Insert Table 2]

The empirical framework for conducting bank-level panel analyses in this study is structured as follows:

$$Lerner_{i,t} = \alpha + \beta MPI_{t-1} + \gamma Controls_{i,t-1} + \delta Macros_{t-1} + \mu_i + \eta t + \varepsilon_{i,t} \quad (4)$$

Where $Lerner_{i,t}$ represents the measure of banking competition at the bank level, quantified by the Lerner index. MPI refers to the Macroprudential Policy Index. The term Controls includes bank-specific control variables, while Macros encompasses macroeconomic time-series variables. To mitigate potential issues of reverse causality, all variables are lagged by one year. Additionally, the model incorporates bank-fixed effects and a time trend to account for unobservable or omitted variables that could influence the results.

4. Empirical Results

4.1.Baseline results

Our regression analysis is detailed in Table 3, which presents the findings across three distinct columns. Each subsequent column progressively incorporates an increased number of bank-related control variables. This approach ensures a thorough consideration of all potential influencers on our outcomes. A consistent and noteworthy trend emerges from the analysis: a robust and positive relationship between macroprudential policies and the Lerner index. The regression coefficients, 0.0014 and 0.0044, are significant at the 5% and 1% levels, respectively. This pattern strongly suggests that the tightening of macroprudential policies is associated with a notable rise in the average Lerner index, implying a decrease in competitive intensity within the banking sector.

In addition to banking-specific factors, our analysis integrates crucial macroeconomic variables such as the growth rates of real GDP, the Consumer Price Index (CPI), and the money supply (M2). The inclusion of real GDP and CPI growth rates allows us to account for overall economic activity, while the M2 growth rate

considers the impact of monetary policy. The integration of these variables enhances the comprehensiveness of our analysis.

Our bank-focused analysis considers several pivotal factors. The size of the bank is evaluated to understand advantages like economies of scale. The loan-to-deposit ratio is analyzed to gauge the bank's lending behavior relative to its deposits. The capital adequacy ratio provides insights into the bank's financial robustness and resilience. The proportion of non-interest income sheds light on the bank's strategic diversification beyond traditional lending activities. The net interest margin is assessed as an indicator of profitability from core banking operations. Lastly, the non-performing loan ratio is crucial for understanding the risk profile of the bank's loan portfolio.

[Insert Table 3]

4.2. Individual macroprudential tools

In refining our initial analysis, which employed the Macroprudential Policy Index (MPI) in its entirety, we delved into the specific components of macroprudential policies to gain a deeper understanding of their effects on bank competition. As shown in Table 4, we examine various individual macroprudential tools while maintaining consistency in other control variables. This approach revealed that seven distinct types of macroprudential policies significantly and positively affect the Lerner index, a measure of competition among banks. These policies include the countercyclical capital buffer (CCB), requiring banks to hold additional capital during high credit growth periods; overall capital requirements (Capital) imposed on banks; limits on the overall credit issued (LCG); restrictions on specific loan types (LoanR); loan-to-value (LTV) ratios, particularly impactful in mortgage lending; regulations pertaining to banks' liquid assets (Liquidity); and rules targeting Systemically Important Financial Institutions (SIFI), essential for financial system stability. This detailed analysis not only aligns with our initial discussion of China's macroprudential practices but also justifies the use of the iMaPP database for specific country analysis. Crucially, these results provide substantial backing for our mechanism analysis, emphasizing the influence of these tools on banking competition.

[Insert Table 4]

4.3.Mechanism analysis

In this subsection, we delve into the mechanisms through which macroprudential policies influence competition among banks. Building on previous research by González (2022), Mirzaei and Moore (2021), and Scalco, Tabak, and Teixeira (2021), we identify three potential factors that could affect banking competition. However, only one appears to be consistent with our observations:

Firstly, we examine the role of Mergers and Acquisitions (M&A). Stricter macroprudential regulations can escalate compliance and risk management costs, particularly burdening smaller or financially weaker banks. Consequently, these banks may resort to merging with or being acquired by larger entities to maintain stability and competitiveness. Such consolidation could reduce the number of market players, potentially diminishing competition. However, as indicated in Table 5, we observe only a minor decline in the number of city commercial banks, while the number of rural commercial banks has increased. This trend suggests that the M&A impact of macroprudential policies may not be the primary driver of the changes we've noted.

[Insert Table 5]

Secondly, we consider Barriers to Entry. More stringent macroprudential regulations can impose higher capital requirements and lending restrictions on new market entrants, making it challenging for new banks to establish and compete. While this could consolidate the market position of existing banks, the continued emergence of new banks implies that entry barriers, though present, may not be critically influencing the sector's dynamics.

Finally, we explore Proactive Risk Management and Return Optimization. In response to rigorous macroprudential regulations, banks may recalibrate their risk-taking strategies, balancing the need to increase marginal returns against reducing marginal costs, all within the prescribed risk limits. This risk management, coupled with asset distribution optimization, could enhance profitability and market positioning.

This hypothesis aligns with our analysis of macroprudential tools in China and the outcomes detailed in Table 4. Our decomposition of the Lerner index reveals that the index's increase is driven by rising marginal revenue and stable marginal costs. Furthermore, the observed decrease in asset growth and increase in income growth, indicative of efficient risk-return management, seem to be in line with the intended effects of China's macroprudential policies. However, the resultant shift in banking competition appears to be an unintended consequence.

In Table 6, we employ rigorous control variables to examine the impact of macroprudential policies on marginal revenue, marginal cost, asset growth, and income growth. The analysis confirms that the increase in the Lerner index results from heightened marginal revenue and unchanged marginal cost, with shifts in asset and income growth underpinning these changes.

[Insert Table 6]

4.4.Exogenous shocks and heterogeneity

In 2016, a pivotal shift occurred in China's macroprudential policy landscape: the transition from a singular dynamic reserve requirement to a more comprehensive Macro Prudential Assessment (MPA) system, introducing a broad array of macroprudential tools. This transition can be considered an exogenous shock to banking competition, as the primary aim of the MPA was to mitigate systemic financial risks without explicitly addressing banking competition. The banks were likely unprepared for this sudden upgrade, as there was no adjustment in behavior noted before 2016. This is evidenced by *the China Monetary Policy Report Q4 2015*, published on February 6th, 2016, which first publicized the MPA upgrade. In contrast, the preceding report (*Q3 2015*, issued on November 6th, 2015) only mentioned the dynamic reserve requirement, indicating that the significant impact of the MPA upgrade only materialized in 2016.

This exogenous shock provides an opportunity for a more causal analysis, especially in examining heterogeneity among banks. We hypothesize that larger banks, those with more substantial assets and typically operating nationwide (a unique feature of China's banking system), would be more significantly impacted by macroprudential

policies. These banks, due to their scale and national reach, are more likely to engage in diverse and profitable ventures, making them particularly susceptible to restrictive macroprudential measures.

To empirically test this, we leverage the 2016 exogenous shock and employ a generalized Difference-in-Differences (DID) approach. Our grouping variable is the log of banks' assets in 2013, ensuring that the classification remains unaffected by the shock. The results, displayed in Table 7, show that the interaction term in Column 1 (did-2016_size_2013) significantly affects the Lerner index. This indicates that larger banks experienced a more pronounced increase in the Lerner index following the shock. In Column 2, an event-study analysis reveals that, apart from in 2016, the coefficients are not significant. This suggests that there was no pre-trend or anticipation of the shock, and that larger banks rapidly adjusted their strategies within 2016, with no prolonged effects observed in 2017 or 2018. Figure 1 illustrates this analysis, clearly showing a jump in the coefficient from 2015 to 2016, without any prior trend.

[Insert Table 7]

[Insert Figure 1]

5. Robustness Check

Our robustness check is divided into two segments. Firstly, we explore alternative measures of the Lerner Index, both through varied calculation methods and the use of different datasets. Secondly, we conduct a city-panel analysis, employing the Herfindahl-Hirschman Index (HHI) as an alternative to the Lerner Index. Overall, these checks affirm that our conclusions are robustly supported by the data.

5.1 Alternative Measures

Adapting the methodology of Jiménez et al. (2013), we calculate a simplified Lerner Index using data on interbank lending rates. The formula employed is as follows:

$$Lerner_{i,t} = \frac{R_t - r_{i,t}}{R_t} \quad (5)$$

where R_t represents is the average interbank lending rate in year t, and $r_{i,t}$ is the deposit interest rate paid by bank *i* in year *t*.

Table 8 showcases the results obtained from this alternate Lerner Index calculation, which hinges on bank interest rates. The data decisively indicate that macroprudential policies exert a significant impact, as evidenced by the substantial increase in the Lerner Index, significant at the 1% level. This reinforces the substantial role of macroprudential policies in molding banking market dynamics.

[Insert Table 8]

In Table 9, we address potential nuances in our original dataset by performing further robustness checks using data from BankFocus. This comprehensive dataset includes extensive financial details from 128 banks. The results gleaned from this expanded analysis corroborate our initial findings, thus solidifying the credibility of our conclusions. The consistency observed across various datasets not only strengthens the reliability of our results but also highlights the pervasive influence of macroprudential policies on banking sector dynamics.

[Insert Table 9]

5.2 Regional Competition

In extending our analysis, we incorporate data on bank branches across 286 prefecture-level cities, enhancing the depth of our investigation into the impact of macroprudential policies on banking competition. This study delves into the intricate competition dynamics among bank branches, acknowledging the evolving landscape shaped by the fintech revolution. Our focus is on the period starting from 2010, a critical juncture when fintech began to emerge, yet physical bank branches remained fundamental to the banking sector. We utilize the Herfindahl-Hirschman Index (HHI) as a key metric to gauge historical competition among banks during this transitional phase.

The Herfindahl-Hirschman Index (HHI) is calculated consistently in various

research contexts. For our study, we construct the HHI at the city-level using data from the CNRDS database, complemented by financial license information of banking branch institutions from the China Banking and Insurance Regulatory Commission (CBIRC)[3]. The HHI is formulated as follows:

$$HHI_{c,t} = \sum_{i=1}^{n} \left(\frac{Branch_{c,i,t}}{Total_{c,t}} \right)^2 \quad (3)$$

where $Branch_{c,i,t}$ signifies the number of branches of bank i in city c during year t, and $Total_{c,t}$ represents the total number of bank branches in city c during year t.

Table 10 employs the System GMM method to present our results, examining the influence of macroprudential policies on banking competition. Whether we group standard errors by city (columns (1) and (2)) or by province (columns (3) and (4)), the findings consistently demonstrate a significant positive effect of macroprudential policies on banking competition. The data indicates an increase in the Herfindahl-Hirschman Index (HHI), suggesting a decrease in competition among bank branches. The specifics of the control variables used in this analysis are detailed in Table 11.

[Insert Table 10]

[Insert Table 11]

6. Conclusion

Our research offers a robust validation of the impacts of macroprudential policies on the competitive landscape of the banking sector, especially within the context of a rapidly evolving banking environment. By integrating detailed data from individual banks and insights into the dynamics of bank branches, our study presents a holistic

[3] The China Banking and Insurance Regulatory Commission (CBIRC) issues financial licenses to various financial entities, including commercial banks, policy banks, and trust companies, among others. Each license is equipped with critical information such as a unique 15-character code, the institution's name, and the license's start and end dates. This unique code functions as an identifier for each commercial bank, facilitating an efficient tracking system. By analyzing this dataset, we can ascertain the number of commercial bank branches that have either opened or ceased operations in a particular city within a given year. This information is instrumental in accurately calculating the Herfindahl-Hirschman Index (HHI), providing valuable insights into the dynamics of banking competition at the city level.

view of the interplay between regulatory changes, technological advancements, and competitive forces in the banking industry.

Employing the Lerner and Herfindahl-Hirschman Indices as key metrics, our comprehensive analysis scrutinizes the competitive dynamics of China's banking sector. Analyzing data from 389 banks across 287 cities, we find compelling evidence that macroprudential policies are associated with a reduction in competitiveness within the industry. Our mechanism analysis reveals that under the influence of these policies, banks tend to adjust their asset allocation and risk management strategies, inadvertently increasing their monopoly power. Utilizing the Difference-in-Differences (DID) approach, our study elucidates the specific effects of these policies. Furthermore, we observe a marked heterogeneity in impact, with larger banks being more significantly affected by macroprudential policies compared to their smaller counterparts.

Although the primary intention of macroprudential policies is to safeguard financial stability, our findings highlight an unintended byproduct: a diminution in banking competition. This revelation suggests that regulatory authorities should thoughtfully consider the challenges confronting smaller banks, aiming to strike a balance between fostering competition and ensuring financial stability, all while safeguarding consumer interests.

In essence, our study enriches the understanding of the repercussions of macroprudential policies in the banking sector. It emphasizes the necessity for well-calibrated regulatory measures that maintain competitiveness in China's banking sector while concurrently prioritizing the overall stability of the financial system.

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Table 1 Summary statistics for bank panel

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
MPI	3,709	3.469	3.079	0	12
lerner	3,186	0.176	0.152	-0.171	0.398
gdp	3,709	7.113	1.807	2.200	10.64
cpi	3,709	2.232	1.012	0.900	5.400
m2_gr	3,709	0.117	0.0329	0.0827	0.206
cap_ratio	3,709	13.96	2.892	11.11	54.09
ldr	3,667	0.684	0.168	0.0511	7.395
nii	3,232	0.00166	0.00181	3.19e-05	0.0259
nim	3,231	0.0239	0.0109	-0.0120	0.154
nploan	3,689	1.890	1.481	0.600	28.44
size	3,353	24.97	1.680	22.26	31.19

Note: The table displays summary statistics for the key variables employed in the bank panel regression models. Columns (1) through (5) provide these summary statistics for the entire sample.

Table 2 Variable definitions and data sources

Variables	Variable Definition	Data Source
cap_ratio	Capital Adequacy Ratios (%)	CNRDS
nii	Non-interest income/total assets	CNRDS
nim	Net interest margin: net interest income/total assets	CNRDS
nploan	Non-performing loan ratios: non-performing loans/total loans	CNRDS
lerner	Lerner Index	CNRDS + Calculated by hand
size	Logarithm of total assets	CNRDS
ldr	Loan Deposit Ratio	CNRDS
MPI	Macroprudential Policy Index	iMaPP
gdp	Real GDP growth (%)	Wind
cpi	CPI growth (%)	Wind
m2_gr	M2 growth	Wind

Note: The table includes detailed definitions of the variables used in the bank panel analysis, accompanied by their corresponding data sources.

Table 3 Baseline results

VARIABLES	(1) lerner	(2) lerner	(3) lerner
L.MPI	0.0023***	0.0024***	0.0041***
	(0.0006)	(0.0007)	(0.0008)
L.gdp	-0.0090***	-0.0091***	-0.0001
	(0.0028)	(0.0028)	(0.0028)
L.cpi	0.0069**	0.0058*	0.0038
	(0.0030)	(0.0031)	(0.0031)
L.m2_gr	0.5746***	0.5821***	1.3833***
	(0.1855)	(0.1867)	(0.2052)
L.size	-0.0399**	-0.0339*	0.0240
	(0.0184)	(0.0178)	(0.0176)
L.ldr		0.0126	-0.0075
		(0.0098)	(0.0152)
L.cap_ratio		0.0022	0.0025**
		(0.0014)	(0.0012)
L.nii			2.2167
			(2.3166)
L.nim			5.4633***
			(0.9214)
L.nploan	-0.0178***	-0.0178***	-0.0160***
	(0.0047)	(0.0046)	(0.0044)
year	-0.0080**	-0.0092**	0.0039
	(0.0038)	(0.0038)	(0.0050)
Constant	17.2897**	19.4647**	-8.5352
	(7.4598)	(7.5218)	(9.7965)
Observations	2,634	2,622	2,599
R-squared	0.3091	0.3106	0.3991
Number of bankcd	396	394	389
Bank FE	YES	YES	YES

Note: This table displays the results for Equation (4), focusing on the annual bank Lerner index (lerner) as the dependent variable. The primary explanatory variable in this analysis is the Macroprudential Policy Index (MPI). To address potential endogeneity issues, all predictors are lagged by one year. Columns (1) to (3) progressively include various bank-level control variables in the regression models. Each regression incorporates bank fixed effects to control for individual bank characteristics. Robust standard errors are presented in parentheses next to the coefficients. The levels of statistical significance are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%.

Table 4 Effect of Individual Macroprudential Tools

VARIABLES	(1) lerner	(2) lerner	(3) lerner	(4) lerner	(5) lerner	(6) lerner	(7) lerner
L.CCB	0.0309**						
	(0.0126)						
L.Capital		0.0309**					
		(0.0126)					
L.LCG			0.0309**				
			(0.0126)				
L.LoanR				0.0160***			
				(0.0042)			
L.LTV					0.0043*		
					(0.0023)		
L.Liquidity						0.0145***	
						(0.0048)	
L.SIFI							0.0212***
							(0.0042)
L.gdp	0.0015	0.0015	0.0015	0.0094***	0.0047	0.0064**	0.0073**
	(0.0023)	(0.0023)	(0.0023)	(0.0030)	(0.0033)	(0.0029)	(0.0028)
L.cpi	0.0117***	0.0117***	0.0117***	-0.0007	0.0088***	0.0131***	0.0110***
	(0.0027)	(0.0027)	(0.0027)	(0.0042)	(0.0026)	(0.0029)	(0.0027)
L.m2_gr	1.0419***	1.0419***	1.0419***	1.4972***	1.3298***	1.7810***	1.7510***
	(0.1947)	(0.1947)	(0.1947)	(0.2046)	(0.2294)	(0.2237)	(0.2161)
L.size	0.0273*	0.0273*	0.0273*	0.0245	0.0236	0.0237	0.0246
	(0.0157)	(0.0157)	(0.0157)	(0.0176)	(0.0178)	(0.0178)	(0.0177)
L.ldr	-0.0072	-0.0072	-0.0072	-0.0071	-0.0066	-0.0078	-0.0074
	(0.0152)	(0.0152)	(0.0152)	(0.0150)	(0.0152)	(0.0159)	(0.0158)
L.cap_ratio	0.0024**	0.0024**	0.0024**	0.0024**	0.0022*	0.0022*	0.0023*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
L.nii	2.6035	2.6035	2.6035	2.2201	2.3509	2.6328	2.6143
	(2.3283)	(2.3283)	(2.3283)	(2.3167)	(2.3189)	(2.3328)	(2.3282)
L.nim	5.3016***	5.3016***	5.3016***	5.4990***	5.3284***	5.3559***	5.2734***
	(0.8426)	(0.8426)	(0.8426)	(0.9297)	(0.8996)	(0.8928)	(0.9003)
L.nploan	-0.0156***	-0.0156***	-0.0156***	-0.0159***	-0.0155***	-0.0160***	-0.0156***
	(0.0044)	(0.0044)	(0.0044)	(0.0045)	(0.0044)	(0.0045)	(0.0043)
year	-	-	-	0.0094*	0.0044	0.0079	0.0096*
				(0.0052)	(0.0054)	(0.0051)	(0.0051)
Constant	-0.8204*	-0.8204*	-0.8204*	-19.8803*	-9.6428	-16.7298*	-20.1415**
	(0.4256)	(0.4256)	(0.4256)	(10.2858)	(10.7849)	(10.1319)	(10.0705)
Observations	2,599	2,599	2,599	2,599	2,599	2,599	2,599
R-squared	0.3941	0.3941	0.3941	0.3973	0.3948	0.3953	0.4001
Number of bankcd	389	389	389	389	389	389	389
Bank FE	YES	YES	YES	YES	YES	YES	YES

Note: This table elucidates the effects of various macroprudential tools, using the yearly bank Lerner index (lerner) as the dependent variable. To address potential endogeneity issues, a one-year lag is applied to all predictor variables. The primary explanatory variables are distinct macroprudential policy instruments. Specifically, “CCB” refers to countercyclical capital buffer requirements, “Capital” to capital adequacy requirements, “LCG” to limits on total credit issuance, “LoanR” to restrictions on certain loan types, “LTV” to loan-to-value ratios, “Liquidity” to various liquidity mandates, and “SIFI” to regulations applicable to systemically important financial institutions. Columns (1) through (7) demonstrate the significant positive impact of these macroprudential tools on the Lerner Index. Each regression in the analysis accounts for bank fixed effects, and robust standard errors are presented in parentheses. The symbols ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 5 Number of Commercial Banks in China

year	large commercial banks	joint-stock commercial banks	city commercial banks	rural commercial banks	private banks
2013	5	12	145	468	0
2014	5	12	133	665	5
2015	5	12	133	859	17
2016	5	12	134	1114	17
2017	5	12	134	1262	17
2018	6	12	131	1365	17
2019	6	12	129	1452	17
2020	6	12	128	1496	19
2021	6	12	128	1596	19
2022	6	12	125	1606	19

Note: The table presents a detailed enumeration of legal entities, categorized according to the various types of commercial banks in China. This compilation covers the period from 2013 to 2022.

Table 6 Mechanism analysis

VARIABLES	(1) P	(2) MC	(3) asset_gr	(4) income_gr
L.MPI	0.0004***	0.0002***	-0.0044***	0.0204***
	(0.0001)	(0.0001)	(0.0015)	(0.0020)
L.gdp	-0.0010***	-0.0008***	-0.0046	-0.0048
	(0.0003)	(0.0003)	(0.0080)	(0.0071)
L.cpi	0.0013**	0.0006	-0.0243***	-0.0041
	(0.0005)	(0.0005)	(0.0065)	(0.0065)
L.m2_gr	0.0299	-0.0342	-1.4561***	3.4980***
	(0.0298)	(0.0295)	(0.5547)	(0.6045)
L.size	0.0091***	0.0060***	-0.4840***	-0.2351***
	(0.0017)	(0.0017)	(0.0673)	(0.0510)
L.ldr	0.0010	0.0011	-0.0676	-0.0952
	(0.0020)	(0.0022)	(0.0610)	(0.0672)
L.cap_ratio	0.0000	-0.0001	0.0041	0.0075***
	(0.0002)	(0.0001)	(0.0033)	(0.0026)
L.nii	0.9947***	0.7288***	1.1074	-10.9369**
	(0.2567)	(0.2387)	(4.8994)	(4.8513)
L.nim	0.5603***	0.3052*	5.9657*	-10.9569***
	(0.0947)	(0.1749)	(3.0428)	(2.4274)
L.nploan	-0.0000	0.0008**	-0.0123***	-0.0281***
	(0.0003)	(0.0004)	(0.0031)	(0.0047)
year	-0.0019***	-0.0015*	0.0415**	0.0377***
	(0.0007)	(0.0008)	(0.0197)	(0.0134)
Constant	3.7169***	2.8420*	-71.1817*	-70.0813***
	(1.3668)	(1.5789)	(38.5726)	(26.5552)
Observations	2,637	2,599	2,655	2,638
R-squared	0.2535	0.0733	0.3304	0.2932
Number of bankcd	390	389	390	390
Bank FE	YES	YES	YES	YES

Note: This table focuses on the mechanisms through which macroprudential policies exert their effects. It examines the impact on marginal revenue, marginal cost, asset growth, and income growth as dependent variables. To mitigate potential endogeneity issues, all predictor variables are lagged by one year. The analysis presented in Columns (1) through (4) indicates that macroprudential tools positively affect both marginal revenue and marginal cost, with a more pronounced influence on marginal revenue. Further analysis of marginal revenue shows that macroprudential policies tend to reduce asset growth while enhancing income growth. Each regression in this study incorporates bank fixed effects to account for individual bank characteristics. Robust standard errors are presented in parentheses alongside the coefficients. The levels of statistical significance are denoted by the symbols ***, **, and *, corresponding to 1%, 5%, and 10% significance levels, respectively.

Table 7 Exogenous shock and heterogeneity

VARIABLES	(1) lerner	(2) lerner	(3) lerner
did_2013_size_2013		-0.0006	-0.0001
		(0.0006)	(0.0012)
did_2014_size_2013		0.0003	0.0006
		(0.0003)	(0.0005)
did_2015_size_2013		-0.0014***	-0.0010
		(0.0004)	(0.0008)
did_2016_size_2013	0.0009**	0.0011***	0.0014**
	(0.0004)	(0.0004)	(0.0005)
did_2017_size_2013			0.0003
			(0.0005)
did_2018_size_2013			0.0006
			(0.0007)
L.size	0.0155	0.0151	0.0157
	(0.0189)	(0.0192)	(0.0201)
L.gdp	0.0064**	0.0049*	0.0019
	(0.0029)	(0.0028)	(0.0031)
L.cpi	0.0125***	0.0052	0.0095
	(0.0027)	(0.0051)	(0.0119)
L.m2_gr	1.5241***	1.2048***	1.2492***
	(0.2202)	(0.2244)	(0.3969)
L.ldr	-0.0001	0.0003	0.0003
	(0.0115)	(0.0113)	(0.0112)
L.cap_ratio	0.0020	0.0020	0.0019
	(0.0013)	(0.0013)	(0.0013)
L.nii	4.0135*	4.2168*	3.7191
	(2.3842)	(2.4786)	(2.5409)
L.nim	5.2356***	5.2549***	5.2379***
	(1.0088)	(1.0352)	(1.0714)
L.nploan	-0.0160***	-0.0159***	-0.0159***
	(0.0048)	(0.0047)	(0.0047)
year	0.0052	0.0043	-0.0035
	(0.0050)	(0.0049)	(0.0071)
Constant	-11.1962	-9.1260	6.5365
	(9.9945)	(9.6674)	(14.0742)
Observations	2,176	2,176	2,176
R-squared	0.4092	0.4129	0.4134
Number of bankcd	272	272	272
Bank FE	YES	YES	YES

Note: This table outlines the results of a Difference-in-Differences (DID) analysis, focusing on the annual bank Lerner Index (lerner) as the dependent variable. To address potential endogeneity, all predictor variables are lagged by one year. The key variable of interest is the interaction between the logarithm of total assets and the year 2016. This interaction aims to capture how the bank size influences the impact of the Macroprudential Policy Index (MPI) upgrade in 2016, marking a shift from differential reserve requirements to the more comprehensive Macroprudential Assessment (MPA) regime. Column (1) displays the primary DID analysis results, while Columns (2) and (3) conduct parallel trend checks and a placebo test, respectively. Each regression model includes bank-specific fixed effects, and robust standard errors are indicated in parentheses. The levels of statistical significance are denoted by ***, **, and *, corresponding to 1%, 5%, and 10% respectively.

Table 8 Robustness: alternative Lerner Index

	(1)	(2)	(3)
VARIABLES	lerner_mean	lerner_mean	lerner_mean
L.MPI	0.0203***	0.0215***	0.0221***
	(0.0049)	(0.0044)	(0.0043)
L.gdp	0.0326*	0.0289	0.0267
	(0.0189)	(0.0193)	(0.0184)
L.cpi	-0.0400*	-0.0668***	-0.0704***
	(0.0240)	(0.0214)	(0.0192)
L.m2_gr	9.0441***	7.8106***	7.8970***
	(0.7941)	(1.1705)	(1.2347)
L.size		-0.3629***	-0.3875***
		(0.0902)	(0.0812)
L.ldr		-0.0473	0.0246
		(0.2866)	(0.2063)
L.cap_ratio		0.0087	0.0013
		(0.0124)	(0.0074)
L.nii		-19.1838	-12.6218
		(18.1681)	(14.9870)
L.nim		0.6745	-2.5784
		(5.1259)	(2.5568)
L.nploan			-0.0032
			(0.0114)
year	0.0367**	0.0777***	0.0784***
	(0.0184)	(0.0240)	(0.0234)
Constant	-75.6442**	-148.9719***	-149.7604***
	(37.3460)	(49.5654)	(47.9991)
Observations	2,714	2,645	2,634
R-squared	0.1072	0.1147	0.2027
Number of bank	404	390	390
Company FE	YES	YES	YES

Note: The table presents results from a robustness check that involves a modification in the computation method of the dependent variable. In this case, the dependent variable is the annual bank Lerner Index, calculated using an alternative approach (lerner_mean). To mitigate potential endogeneity issues, a one-year lag is applied to all predictor variables. The primary explanatory variable examined is the Macroprudential Policy Index (MPI). Columns (1) to (3) progressively incorporate bank-specific control variables into the analysis. Each regression model in the table includes bank-specific fixed effects. Robust standard errors are enclosed in parentheses. The levels of statistical significance are indicated by the symbols ***, **, and *, corresponding to 1%, 5%, and 10% levels of significance, respectively.

Table 9 Robustness: alternative bank database

	(1)	(2)	(3)
VARIABLES	lerner	lerner	lerner
L.MPI	0.0010*	0.0031***	0.0034***
	(0.0005)	(0.0006)	(0.0005)
L.gdp	-0.0037***	-0.0046***	-0.0054***
	(0.0012)	(0.0008)	(0.0008)
L.cpi	-0.0054**	-0.0091***	-0.0099***
	(0.0024)	(0.0018)	(0.0019)
L.m2_gr	-0.3418***	-0.3226**	-0.3493**
	(0.1023)	(0.1256)	(0.1353)
L.size		-0.0151	-0.0296**
		(0.0134)	(0.0128)
L.ldr		-0.0281	-0.0353
		(0.0387)	(0.0320)
L.cap_ratio		0.0035***	0.0037***
		(0.0008)	(0.0008)
L.nii		0.0389***	0.0388***
		(0.0057)	(0.0060)
L.nim		0.0276***	0.0268***
		(0.0039)	(0.0041)
L.nploan			-0.0050***
			(0.0011)
L.liquidity			-0.0003
			(0.0002)
year	-0.0052***	0.0014	0.0033
	(0.0014)	(0.0027)	(0.0023)
Constant	10.8522***	-2.0552	-5.4668
	(2.8908)	(5.2172)	(4.4544)
Observations	1,000	866	821
R-squared	0.0239	0.1905	0.2391
Number of bank	128	116	115
Company FE	YES	YES	YES

Note: This table outlines the results of a robustness test conducted by transitioning the bank database from CNRDS to BankFocus. The focal point of the analysis is the annual bank Lerner Index (lerner) as the dependent variable. To address potential endogeneity, all explanatory variables are lagged by one year. The main variable of interest in this assessment is the Macroprudential Policy Index (MPI). Across Columns (1) to (3), bank-level control variables are sequentially integrated into the models. Each regression model incorporates bank-specific fixed effects. Robust standard errors are detailed within parentheses. The levels of statistical significance are denoted as ***, **, and *, representing thresholds of 1%, 5%, and 10%, respectively.

Table 10 Robustness check: City Panel GMM

	(1)	(2)	(3)	(4)
VARIABLES	HHI	HHI	HHI	HHI
L.HHI	0.9642***	0.9453***	0.9642***	0.9453***
	(0.1415)	(0.1606)	(0.1841)	(0.1795)
L2.HHI	-0.1638	-0.1564	-0.1638	-0.1564
	(0.1217)	(0.1410)	(0.1606)	(0.1604)
L.MPI	0.0004***	0.0003*	0.0004**	0.0003**
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
L.gdp_gr		-0.0012		-0.0012
		(0.0010)		(0.0011)
L.cpi		0.0004		0.0004
		(0.0005)		(0.0006)
L.m2_gr		0.1058***		0.1058*
		(0.0347)		(0.0554)
L.r_consumption	0.0726*	0.0613	0.0726	0.0613
	(0.0393)	(0.0465)	(0.0530)	(0.0531)
L.l_ex_contract	-0.0042*	0.0009	-0.0042	0.0009
	(0.0026)	(0.0027)	(0.0033)	(0.0027)
L.r_ex_fund	3.4789**	1.4651	3.4789*	1.4651
	(1.4260)	(1.3984)	(1.8586)	(1.4612)
L.r_city_deposit	-0.0399***	-0.0370***	-0.0399**	-0.0370**
	(0.0131)	(0.0114)	(0.0176)	(0.0162)
L.r_city_loan	0.0307**	0.0229*	0.0307*	0.0229
	(0.0137)	(0.0123)	(0.0178)	(0.0156)
L.l_ind_firms	-0.0003	-0.0045	-0.0003	-0.0045
	(0.0041)	(0.0045)	(0.0036)	(0.0052)
L.r_fiscal_income	-0.2389**	-0.1569	-0.2389*	-0.1569
	(0.1156)	(0.1431)	(0.1445)	(0.1617)
L.r_fiscal_expen	0.1396**	0.1190**	0.1396*	0.1190*
	(0.0628)	(0.0558)	(0.0715)	(0.0667)
L.r_fix_inv	-0.0290**	-0.0213*	-0.0290	-0.0213
	(0.0136)	(0.0129)	(0.0184)	(0.0179)
L.l_people	-0.0150**	-0.0125*	-0.0150*	-0.0125
	(0.0076)	(0.0073)	(0.0090)	(0.0095)
Constant	0.1316***	0.1317***	0.1316**	0.1317*
	(0.0475)	(0.0498)	(0.0602)	(0.0710)
AR(1) test – p.value	0.000	0.000	0.000	0.001
AR(2) test – p.value	0.272	0.308	0.360	0.350
Hansen test – p.value	1.000	1.000	1.000	1.000

Observations	3,700	3,694	3,700	3,694
Number of city	286	286	286	286
Company FE	YES	YES	YES	YES

Note: The table displays results from a city panel analysis utilizing the System Generalized Method of Moments (System GMM) methodology. The dependent variable analyzed is the yearly Herfindahl-Hirschman Index (HHI) specific to each city. To mitigate potential endogeneity, all explanatory variables are lagged by one year. For Columns (1) and (2), robust standard errors are indicated within parentheses, while Columns (3) and (4) feature standard errors that are clustered at the provincial level, also presented within parentheses. The levels of statistical significance are marked by ***, **, and *, corresponding to significance thresholds of 1%, 5%, and 10%, respectively.

Table 11 City Panel: Variable Definition and data sources.

Variables	Variable Definition	Data source
HHI	HHI	CNRDS
gdp_gr	Regional GDP growth	CNRDS
MPI	Macroprudential Policy Index	iMaPP
cpi	CPI growth	Wind
m2_gr	M2 growth	Wind
r_consumption	Total retail sales of regional social consumer goods /Regional GDP	CNRDS
l_ex_contract	Logarithm of regional foreign trade contracts	CNRDS
r_ex_fund	Amount of foreign capital actually utilized by the region / Regional GDP	CNRDS
r_city_deposit	Regional deposit/ Regional GDP	CNRDS
r_city_loan	Regional loan/ Regional GDP	CNRDS
l_ind_firms	Logarithm of regional number of industrial enterprises above designated size	CNRDS
r_fiscal_income	Regional fiscal income/ Regional GDP	CNRDS
r_fiscal_expen	Regional fiscal expenditure/ Regional GDP	CNRDS
r_fix_inv	Regional fixed assets investment Regional GDP	CNRDS
l_people	Logarithm of regional population	CNRDS

Note: The table includes detailed definitions of the variables used in the city panel analysis, accompanied by their corresponding data sources.

Figure 1 Exogenous Shock DID analysis