Banking Innovations in China: Evidence and Welfare Implications*

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Abstract

Understanding the impacts of new technology and innovations on the banking sector is important and of growing interest. However, there is limited research on the detailed channels of these impacts and, consequently, their evaluations with respect to the aggregate welfare implications. We contribute in this regard both empirically and quantitatively. Using the Chinese bank panel dataset, we construct a new measure of overall banking innovations, and document that banking innovations can reduce marginal net costs, improve efficiency, and increase bank risk-taking. Our findings are robust under a battery of sensitivity checks. We then construct a novel quantitative banking model in which banks with heterogeneous capital choose investment in innovation and risky lending, face regulations on capital requirements, and have limited liability. Our quantitative analysis indicates that an improvement in aggregate new technology can reduce financial intermediation costs and social dead-weight losses. However, such an improvement will also change the bank's risk consideration and exacerbate moral hazard problems with reduced costs. Closely related, we also find new implications for R&D investment credit and capital requirement policies.

Keywords banking innovations, bank risk-taking, welfare effects, general equilibrium

JEL Classification D82, G21, H81

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1 Introduction

The impact of new technology on productivity and economic growth has long been a central topic for economists and policymakers. For the banking and financial intermediation sector, banking innovations also have important impacts. However, there remains a limited understanding of the channels through which banking innovations can affect banks' operations and, consequently, impact welfare. For developing countries in particular, further understanding of banks' efficiency and dynamism could have critical implications for economic development and growth (Beck and Levine, 2018, Jones, 2011). Our paper contributes to these issues.

We study the impacts of banking innovations both empirically and quantitatively.[1] Using bank-level data sets from China, we find that banking innovations can improve efficiency, primarily by reducing non-interest costs, but they do not have so much impact on deposit costs and loan revenues. Thus, the costs of financial intermediation can be reduced when technology advances in the banking sector, consistent with Diamond (1984) and Philippon (2010). We further analyze the impacts of banking innovations on individual banks' lending and risk-taking decisions as well as the general equilibrium effects when banks interact with borrowers and other banks. We construct and estimate a novel structural model and study the aggregate welfare implications of banking innovations. Our quantitative exercises suggest several new insights to the literature.

In our empirical analysis, we first construct bank-level panel data for China. In particular, Chinese commercial banks in the last two decades have improved their efficiency and profitability by investing in Research & Development (R&D), innovative information technology (IT), and other digital banking services and human capital-related investments. We collect data based on the China Stock Market & Accounting Research (CSMAR) database, which contains banks' balance sheet and income statement information. In addition, we manually collect information on banks' IT investments and R&D investments (see Appendix A for more details). We proxy banking innovations by capitalizing various investments in innovation at the bank level in the spirit of Peters and Taylor (2017). We also construct a patent-based measurement of banking innovation as a robustness check. We focus on bank performance with respect to loans and deposits by constructing bank markups on loans and estimating bank cost structure for interest-rates-related and non-interest-rates-related costs.[2]

[1]Banking innovations encompass a wide range of advancements and technological improvements that banks adopted to enhance their operations, customer experiences, and overall performance. Our definition of banking innovation includes technological innovations, changes in bank business credit models, and risk management improvements, excluding new bank products for depositors and individual customers. Thakor (2020) provides an excellent review of the definitions and implications of banking innovations.

[2]Non-interest-rates-related costs contain monitoring and/or loan issuance costs, daily operating costs, labor costs, and other capital costs. Our approach follows Berger et al. (2008) and, more recently, Corbae and D'Erasmo (2021).

In our bank-level panel data, we find that an increase in the initial level of banking innovation is associated with a significant, later reduction in marginal non-interest costs, which may further increase loan markups. In addition, banking innovations are more likely to induce higher risk-taking. We include a rich set of controls, including bank-fixed effects, time-fixed effects, and bank-level characteristics. Our results are robust to a battery of checks. We further confirm our results by using an instrument-variable approach. We exploit variations in individual banks' initial exposure to changes in national college graduates as an instrument for a bank's innovation because different banks tend to have different compositions of labor skills in their workforce. We also use patent data to classify banking innovation. We find consistent patterns in which the patent-based measurement of banking innovation significantly reduces banks' marginal net costs.

Motivated by our empirical findings, we investigate the impacts of banking innovations on banks' efficiency and the resulting aggregate welfare implications through a novel structural model. Banks are heterogeneous in their initial capital and deposits. Banks also differ in their innovation efficiency: higher efficiency can generate higher successful innovation rates for a given level of R&D spending. In addition to R&D investment, banks choose loan portfolios of safe and risky borrowers. Banks are subject to the government's Capital Adequacy Ratio (CAR) requirement, which regulates the risks of a bank's asset side, and adverse shocks may lead to negative equity and bankruptcy. We assume banks have limited liability, and the government provides deposit insurance to households in the case of bank bankruptcy.

We then calibrate the model to fit bank-level data moments. The model can deliver a reasonably good fit to our empirical patterns. For instance, the mean and dispersion of markup rates for banks can be accounted for quite well, which is crucial to discipline banks' cost structures and can have an important influence on aggregate efficiency. The model can also produce positive correlations between R&D investment and banks' profitability, as observed in our empirical analysis.

Based on the quantitative model, we study the aggregate impacts of improving technologies in the banking sector. We find that when aggregate innovation efficiency increases, an individual bank reduces loan issuance costs for both fixed and variable costs. These reductions have an important consequence: holding banks' overall activities unchanged, improved innovation efficiency lowers a bank's loss (induced by non-performing loans) conditional on bankruptcy, consistent with our previous empirical findings. When enjoying better technologies, the bank re-adjusts investment portfolios by increasing its optimal R&D spending and shifting more to risky lending on the margin. This risk-shifting is at the cost of moral hazard because of the deposit insurance, and it increases with a higher aggregate innovation efficiency. In the general equilibrium, individual banks interact with each other, and the equilibrium effect is quantitatively important, accounting for approximately half of the changes in the loan market.

Welfare analysis suggests that an increase in aggregate innovation efficiency improves total social welfare due to reduced financial intermediation costs. However, banks also increase risk-taking activities, leading to a higher social deadweight loss. Quantitatively, both the increased moral hazard problem and social deadweight loss are dominated by reduced costs, resulting in a net increase in social welfare. Therefore, in addition to our empirical analysis, our structural model identifies the detailed channels through which technological innovation impacts the banking sector.

We further explore implications for two R&D-related policies. Specifically, we evaluate the impacts of R&D investment tax-credit policy, which is widely adopted in many countries, within our quantitative framework. We introduce a 20% subsidy for R&D investment in the benchmark economy, which is financed by lump-sum tax from households. Our results show that the policy reduces total loan issuance costs by approximately 12%. Meanwhile, the total effect on social welfare is modest, only about 0.03%. This is because banks re-adjust their loan portfolios toward risky assets, resulting in a higher social deadweight loss. Thus, the tax-credit subsidy policy should be considered more prudent due to banks' risk-shifting incentives.

The second R&D-related policy of interest is the CAR requirement. We analyze the effects of changing the CAR requirement when banks have the R&D investment margin. Our results indicate that a tightened CAR regulation enhances social welfare because the policy depresses the bank's risk-shifting behaviors in portfolio adjustments. However, in the optimal re-balancing investment, banks also reduce investment in R&D since the shadow cost of initial capital becomes higher. Consequently, bankruptcy risk decreases, but the average loss conditional on bankruptcy increases. Overall, the first effect dominates, and total social welfare increases.

These policy experiments indicate that the banking innovation channel is a vital margin to consider, despite the little attention it receives in the literature. In turn, our paper promotes a better understanding of the policy and welfare implications when banks are affected by technological progress.

Related literature First, our paper contributes to existing empirical studies by further understanding the impacts of innovation within the banking industry.[3] The empirical banking innovation literature typically explores the implications of a specific FinTech innovation or technological adoption; however, the underlying channels through which banking innovation affects banks' behavior and performance remain unclear.[4] To address this gap in the literature,

[3]There is a broad literature on the impacts of innovation and new technology (e.g., Acemoglu and Restrepo, 2020, Aghion and Howitt, 1992, Autor et al., 2003, Romer, 1990).

[4]Philippon (2016) summarizes the potential impacts of FinTech innovation on the finance industry. Early research such as Berger (2003) provides descriptive evidence of banks' adoptions of new IT and financial technologies and documents the possibilities of cost reduction and increasing lending capacities. Banking innovation may benefit banks through many channels, such as reducing information asymmetry (De Nicolo et al., 2021), raising

we decompose banks' cost structure so we may offer a new perspective. Our investigation of the detailed channels through which the innovations affect banks' efficiency are also in line with Diamond (1984) and Philippon (2015).

Our paper also provides a new comprehensive measurement of banking innovation from a different perspective. Banking innovations contain digital banking, IT, human capital development, and a wide range of technology implications. However, it is difficult to gauge and measure the functions for various technologies in the banking sector. Thus, the existing literature typically relies on IT investments as a starting point to analyze banking innovation.[5] By capitalizing banks' IT expenses and incorporating banks' attempts to train employees and provide digital banking services, we construct a comprehensive measurement of banking innovation that follows the perpetual inventory method of Peters and Taylor (2017) (see Appendix A for details of this method). More recently, Chen et al. (2019), Fu and Mishra (2022), and Jiang et al. (2022c) classify banking innovations by using taxonomies to classify information from patents across different categories of innovation activities. Likewise, as a robustness check, we also consider a patent-based measurement of banking innovation following the literature.

Importantly, our quantitative model with heterogeneous banks contributes to the theoretical and quantitative banking studies. For instance, Hellmann et al. (2000) highlights the theoretical effects of banking policy changes on moral hazard and welfare. Boyd and De Nicolo (2005) and Martinez-Miera and Repullo (2010) meanwhile focus more on the relationship between bank competition and profitability with their respective theoretical studies. Also, Corbae and D'Erasmo (2021) study banking industry dynamics in business cycles quantitatively, and Li et al. (2022) study the impacts of Chinese banking regulation changes over business cycles. Our paper introduces a novel cost structure and R&D investment that can alter banks' costs. Our structural framework builds on influential theory in Diamond (1984) and Philippon (2010), and is closely related to the macro and growth literature (e.g., Acemoglu et al., 2018, Akcigit and Kerr, 2018, Klette and Kortum, 2004). Our paper differs from these existing quantitative banking studies by focusing on the impacts of banking innovations on individual bank performance and aggregate social welfare.

Our paper is also related to the recent strand of literature that focuses on China's banking system and its interaction with regulations and monetary policies. Cong et al. (2019) use loan-

loan rates charging (Buchak et al., 2018), enhancing lending efficiency (Berg et al., 2020, Björkegren and Grissen, 2020, Branzoli et al., 2021, Frost et al., 2019, Fuster et al., 2019, Jiang et al., 2022b, Kwan et al., 2021), lowering screening and monitoring costs (Pierri and Timmer, 2022), lowering expenses and transaction costs (Vives, 2019), and promoting social welfare by enabling lower startup costs for entrepreneurship (Ahnert et al., 2021). Moreover, banking innovation may intensify competition (Vives and Ye, 2023) and unintentionally increase bank risk-taking and fragility (Beck et al., 2016, Zhao et al., 2023). Banking innovation may also cause macroeconomic impacts on the real economy through monetary policy transmission (De Fiore et al., 2023, Hasan et al., 2023, Modi et al., 2022) or resource misallocation (Jiang et al., 2022a).

[5] Kwan et al. (2021) and Branzoli et al. (2023) document the importance of IT investment as a growth engine for banking.

level data and find that credit expansion during China's large-scale fiscal stimulus in 2009-2010 disproportionally favored SOEs despite their lower average product of capital. Gao et al. (2019) studies the effect of bank entry deregulation in China by using loan-level data, and find that following deregulation, new entrant banks' preference for lending to SOEs over more productive private firms leads to higher credit misallocation, which mitigates the potential benefits of bank competition. Chen et al. (2022) investigate the role of bank wholesale funding for China's monetary policy transmission based on empirical evidence by using bank-level datasets. Their analysis suggests that wholesale funding via interbank certificates of deposit facilitates the monetary policy transmission towards non-state banks, but also unintentionally increases their systemic risks. Li et al. (2022) meanwhile exploit loan-level data and study both empirically and quantitatively the impacts of implementing Basel III capital regulation on banks' risk-taking. They find that a bank's risk management on the loan portfolio provides an important channel for monetary policy transmission. Finally, Hasan et al. (2023) find that lending-related banking innovation amplifies monetary policy transmission through bank lending channels.[6] Unlike these papers, we focus on investigating banking innovation and its aggregate and distributional impacts, both empirically and quantitatively.

The rest of this paper is organized as follows. In Section 2, we present our empirical facts and show how banking innovations can impact bank cost structure, efficiency, and risk-taking. In Section 3, we introduce a theoretical model with heterogeneous banks in which investments in innovation and loan portfolio decisions are made by banks subject to capital requirement constraints. In Section 4, we solve the quantitative model and calibrate it to China's bank panel data. In Section 5, we implement numerical simulations and study welfare implications of banking innovations, and we conclude this paper with Section 6.

2 Empirical Analysis

In this section, we first describe our data set and variable constructions. We then document a negative relationship between banking innovation and banks' marginal non-interest costs and a positive relationship between banking innovation and bank loan markups. We show these relationships using simple regressions and more rigorous econometric analysis that includes a rich set of controls and instrumental variables. In addition, we find that banks with a higher level of banking innovation, all else equal, tend to take more risks. Finally, we confirm our results with several robustness analyses, for which we include using alternative patent-based measurements

[6] Frost et al. (2019), Liu et al. (2022) and Huang et al. (2023) document the interaction between BigTech lending and conventional bank loan lending. They find that BigTech lending, which focuses on SME and consumer loans, does not directly compete with traditional banks. Thus, we focus on banking innovation within the traditional banking sector.

of banking innovation, alternative bank efficiency measures, and different econometric methods.

2.1 Data and Variables

To construct our bank-level panel dataset, we use two major sources. We obtain banks' balance sheet information from the China Stock Market & Accounting Research (CSMAR) database, which includes loans, deposits, and other detailed balance-sheet characteristics. We manually collect other variables from banks' annual reports, including interest-related income, cost structures, and IT expenses, among others. We also obtain information on 310 banks from 2008 to 2021, which accounts for more than 85% of China's total bank assets.

Bank investments in innovation cover not only R&D (mostly IT-related) expenses but also expenses related to talent employee training programs (e.g., platform developments, digital banking services). To incorporate various technology investments, we construct a comprehensive measure of banking innovation by accumulating various investments in innovations. Using the perpetual inventory method, we capitalize banks' IT expenses as knowledge capital and a small fraction of general administrative expenses as organizational capital. We then sum these two expenses with on-the-balance-sheet intangible assets (e.g., banks' patents, special franchises). Such a measurement represents capitalized investments in innovation.[7] The litersture suggests that knowledge and organizational capital may influence firms' operating efficiency and productivity (e.g., Bartel et al. (2007), Crespi et al. (2007)), and following De Ridder (2021) and Corrado et al. (2022), we believe that such a measurement can best reflect overall banking innovation in China. Following the FinTech innovation literature, we also construct a patent-based measurement of banking innovation as a robustness check in Section 2.4.

To examine the main channels through which bank investments in innovation affect bank performance, we focus on bank deposits and loans, which constitute the primary financial activities in China's banking sector.

There are two types of bank costs in general: interest-related costs (or cost of funds) and non-interest costs. We compute interest-related costs as interest paid to deposits and central bank borrowing, and compute non-interest cost by estimating the marginal cost of producing a loan, which is derived from an estimate of marginal net expenses defined as marginal non-interest expenses net of marginal non-interest income. We employ the trans-log regression model to construct these marginal costs following the standard empirical banking literature (e.g., Berger et al. (2008)). We follow Corbae and D'Erasmo (2021) and compute loan markups as the ratio between the interest return on loans and the sum of interest-related and non-interest costs. The details of variable constructions are described in Appendix A.

[7]See Babus et al. (2023), Corrado et al. (2020), Kogan and Papanikolaou (2019), Peters and Taylor (2017), among others.

Figure 1 plots the asset-weighted aggregate level of loan markups along with its components. The time series is from 2008 to 2021. We calculate the asset-weighted average by using the individual bank's assets over total assets in each period as the weight. Consistent with Corbae and D'Erasmo (2021), average loan markups have risen since banks made large efforts to increase their profitability and strengthen their competitive advantages during the sample periods. The average interest return on loans and the average cost of funds (or interest-related costs) are relatively stable, while the average non-interest costs measured by the average marginal non-interest net expenses present a clear declining trend. This implies that the change in the non-interest net expenses is the primary driving force of the increase in loan markups.

The average cost of funds remains relatively stable even if China experiences a falling interest rate, probably since the People's Bank of China (PBOC) has regulated bank deposit rates for a long time, thus prohibiting commercial banks from adjusting their deposit rates flexibly. The average interest return on loans, despite fluctuations, declines from 7% to 5% in the sample period due to expansionary monetary policies in place during economic slowdown episodes. Notably, the trend of marginal net expense has consistently declined over the sample period, which could reflect banks' incentives to improve efficiency and enhance profitability via investments in innovation.[8]

[8] We control the financial asset trading related to off-balance sheet products when we construct the marginal net expenses using a trans-log function. Thus, the declining trend for marginal net expenses that starts from 2017 may not be driven by the New Capital Regulation on off-balance sheet, non-standard products in China.

Figure 1: Average Loan Markup and its Components

NOTE: This figure plots the asset-weighted average level of loan markups and their components. The top left panel is the average loan markup; the top right panel is the interest return on loans from the previous year; the bottom left panel is the cost of funds measured as interest paid to deposits and central bank over total deposits and central bank borrowings; the bottom right panel is marginal net expenses derived from a trans-log function. We use an individual bank's assets over aggregate bank assets as weights for aggregate averages. The pattern remains valid when we construct the aggregate variables in three alternative ways: simple average, weighted by state-owned banks (top 5) only, and top 10 banks only. Figure A.3 in the Appendix presents our results. For an individual bank's markup, we define *1+markup* as the ratio between the interest return on loans and the sum of the cost of funds and non-interest net expenses. The magnitude reflects the percentage point.

Table 1 presents the summary statistics for the main variables. Banking innovation is measured by capitalizing investments in innovation and classifying bank patent applications. Markups on bank loans and their decomposition are constructed following Corbae and D'Erasmo (2021). The average loan rate is 6.773%, the average cost of funds is 2.003%, and the average marginal net expense is 1.406%. These percentages suggest that the average markup of loan price over marginal costs is 98.684%.

Banks' investments in innovation could also interact with banks' investments in risky loan assets and, therefore, banks' risk-taking behaviors. Recent studies have proposed various bank risk-taking measurement methods from different perspectives.With bank-level data, the most frequently used proxies are the non-performing loans ratio and the risk-weighted assets share. The non-performing loans ratio can reflect the quality of bank loan assets and the ex-post credit risk that the bank bears. The risk-weighted asset ratio measures the bank's ex-ante risk-taking, including loan risks and market risks associated with other assets. We use the latter one as an alternative measurement of bank risk-taking for our robustness checks. Also, Table A.3 in the Appendix also provides summary statistics for different types of banks, including state and non-state banks. The summary statistics indicate that banking innovation, measured by capitalized investments in innovation or patents, is primarily concentrated within state banks.[9]

Table 1: Summary Statistics for Main Variables

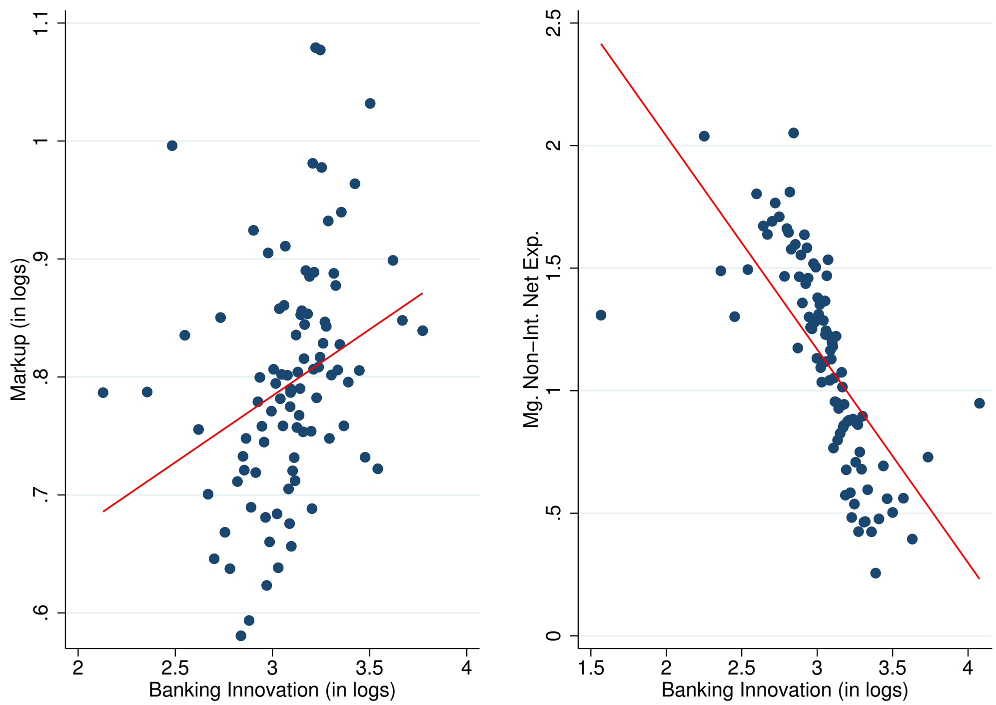
	mean	sd	p50	p25	p75
Banking Innovation	1.907	1.472	1.602	0.852	2.545
Patents-based Banking Innovation	27.490	39.595	6.000	2.000	36.000
Marginal Net Expenses (%)	1.406	1.005	1.406	0.739	1.992
Loan Markup (%)	98.684	236.030	75.156	39.059	114.032
Interest Return on Loans (%)	6.773	3.313	6.507	5.367	7.845
Cost of Funds (%)	2.003	0.685	1.930	1.594	2.270
Capital Adequacy Ratio (%)	15.090	6.459	13.670	12.290	15.650
Non-performing Loan Ratio (%)	1.694	1.261	1.470	0.960	1.990
Risk-weighted Asset Share	0.529	1.072	0.000	0.000	1.192
Size (log)	6.499	1.867	6.343	5.307	7.469
Leverage Ratio (%)	8.581	4.047	7.856	6.464	9.355
Profit/Asset (%)	1.515	0.835	1.363	0.982	1.893
Liquidity Asset Share (%)	58.639	21.564	54.070	44.530	67.720
Interbank Liability Share (%)	6.426	8.006	3.323	0.454	9.749
Loan Asset Share (%)	49.961	11.640	50.797	42.735	57.372

NOTE: The sample size is 2066, and the time span is 2008-2021. All variables are defined in Table A.2 in the Appendix.

The left panel in Figure 2 indicates a clear positive relationship between banking innovation and loan markups. The right panel displays a significant negative relationship between banking innovation and marginal non-interest net expenses. We next proceed with further econometric analysis.

[9]State banks exhibit higher loan markups, lower interest returns on loans and lower risk-taking behaviors, but also smaller marginal net expenses and cost of funds. In contrast, non-state banks demonstrate comparatively lower levels of innovation and smaller markups on loans, with larger interest returns on loans, more risk-taking, and higher marginal net expenses and costs of funds. Further analysis of the heterogeneous impacts of banking innovation across different ownership types is beyond our scope in this paper, as we primarily focus on overall banking innovation and its welfare implications. We leave these ideas for future research.

Figure 2: Loan Markups, Marginal Net Expenses and Banking Innovation



NOTE: The left panel shows the scatter plots between banking innovation and loan markups; the right panel shows the scatter plots between banking innovation and marginal non-interest net expenses. Banking innovation is measured by capitalizing innovative-related expenses. The figure depicts the scatter plots by controlling bank fixed effects.

2.2 Econometric Specification

We run panel regressions to document how innovative technology affects bank profitability structure, including costs of funds and marginal non-interest net expenses, and bank risk-taking behaviors. For this purpose, we estimate the following empirical specification:

$$Y_{i,t} = \beta \cdot \text{Innovation}_{i,t-1} + \Gamma' \cdot \mathbf{X}_{i,t-1} + \Lambda' \cdot \mathbf{Z}_{t-1} + \delta_i + \varepsilon_{it}, \tag{1}$$

where $Y_{i,t}$ is the variable of interest for bank i at year t; $\text{Innovation}_{i,t-1}$ is the level of innovation measured by the logarithm of the cumulative capitalized investments of bank i in innovation at year $t-1$; $X_{i,t-1}$ controls for bank-level balance sheet characteristics such as loan share of total assets, liquidity ratio (liquid assets over liquid liabilities), and interbank liability over total liability for bank i at year $t-1$. We add a set of aggregate indicators in Z_{t-1}, including GDP growth, M2 growth, and a one-year benchmark deposit rate set by the People's Bank of China at year $t-1$. We control for bank-fixed effects (δ_i), and we also include time-fixed effects (δ_t) in the following as a robustness check.

One concern with our panel regression analysis is the potential endogeneity that stems from bank heterogeneity along various dimensions as well as unobservable or omitted factors simultaneously affecting innovation and outcome variables. To mitigate endogeneity concerns, we include a rich set of bank-level controls, lag all independent variables by one period in the baseline regression, and employ an instrumental variable (IV) approach as an alternative. We construct our instrument from a bank's initial employee share with graduate degrees multiplied by the national-level growth rate of graduate students who possess a Master's Degree in Science (MSc). Since the innovation process is usually associated with human capital development, key talents and IT employees can crucially contribute to innovation in the banking industry (Philippon, 2015, 2016). This instrument for bank-level graduate employee share relfects the interaction of the national STEM graduate growth rate with bank-level initial exposure, and allows us to avoid any bank-level bias arising from measurement errors.

2.3 Results

2.3.1 Effects of banking innovation on loan markups and their decomposition

Banking innovation may not only reduce costs to improve loan profitability but also help banks attract more deposits at a lower cost or charge higher interest rates and engage higher loan returns from lending activities. To see this, we decompose loan markups into three components: interest returns on loans, interest-related costs of funds, and marginal non-interest net expenses. We subsequently conduct regression on banking innovation for each variable by adding aggregate controls or time-fixed effects. Since not all banks report sufficient information on cost structures, interest incomes, and interest expenses, the sample size is restricted and smaller for the following analysis.

We implement the unbalanced bank panel regression based on the specification in (1). Table 2 reports our baseline estimation results for the markup on bank loans and its decomposition. Specifically, Column (1) indicates that banking innovation significantly reduces marginal non-interest net expenses, with a point estimate of -0.510 at a 1% significance level. This coefficient value indicates that a 1% increase in a bank's innovation level is associated with a 0.510% decrease in its marginal cost of producing a loan while controlling for bank-level characteristics and bank-fixed effects. The results remain valid in Columns (2)-(3) when aggregate controls or time-fixed effects are considered. Column (4) shows that banking innovation significantly raises loan markups, as a 1% increase in the initial bank's innovation level is associated with a 0.132% increase in markups on bank loans. Columns (5)-(6) show similar results when we consider aggregate controls or time-fixed effects. Columns (7)-(9) indicate that there's no clear correlation between interest return on loans and banking innovation, and Columns (10)-(12) show that the measured increase in markups is substantially dampened through higher interest-related costs of funds. These results suggest that the increasing loan markup is influenced by reducing marginal net expenses, while the impact of banking innovation on the other two interest-related terms is ambiguous. That is, banking innovation is significantly associated with lower marginal non-interest expenses rather than higher loan returns or smaller interest-related costs of funds. Therefore, the marginal cost-reducing channel dominates the resulting increase in markups on bank loans. Our results remain robust for alternative empirical specifications and IV estimations. Appendix B provides more detailed discussions.

The marginal non-interest costs of producing a loan contain monitoring, operating, and management costs associated with loan production. This suggests that innovative practices and technological applications help reduce loan origination and monitoring costs. For instance, banks may invest in mobile app development to make their business less branch-reliant, reducing bank operating costs.[10] Banks may also invest in advanced equipment to replace redundant labor, reducing labor costs. Moreover, Chinese commercial banks choose to build credit risk evaluation systems using big data and artificial intelligence technology to combine internal and external data and monitor borrowers' cash flow, improving banks' monitoring efficiency.

We show that a higher initial level of banking innovation results in better bank loan profitability by significantly reducing marginal non-interest net expenses. Recall that we measure the overall level of banking innovation by accumulating capitalized IT expenses and other possible innovative-related expenses. Our baseline results are in line with findings in the corporate finance literature that focus on intangible capital. By capitalizing firms' R&D expenses and

[10]Being less branch-reliant may help reduce the frequency of customer branch visits, leading to lower demand for customer service staff.

Table 2: Effects of Banking Innovation: Loan Markups Decomposition

	Marginal Non-interest Net Expense			Loan Markups			Interest Return on Loans			Interest-related Cost of Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation$_{i,t-1}$	-0.510***	-0.490***	-0.382***	0.132***	0.227***	0.176**	-0.358**	0.656**	0.393	0.220***	0.414***	0.298***
	(0.070)	(0.108)	(0.120)	(0.044)	(0.068)	(0.078)	(0.176)	(0.260)	(0.310)	(0.047)	(0.065)	(0.076)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Time FEs	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
$\mathbf{R}^2$	0.710	0.710	0.755	0.770	0.772	0.794	0.888	0.897	0.900	0.652	0.723	0.743
Observations	715	715	715	715	715	715	715	715	715	715	715	715

NOTE: This table reports the estimated results of regressing loan markups and their components on banking innovation. Loan markups take the logarithm with eliminating negative values, consistent with Corbae and D'Erasmo (2021). Bank-level controls, bank- and year-fixed effects, and aggregate-level controls are specified when indicated. We run baseline regressions for each variable of interest and add aggregate controls or time FEs, respectively. The numbers in parentheses indicate robust standard errors. Asterisks denote levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

organizational-related expenses, this strand of literature typically finds that intangible capital could affect non-financial firms' markups by reducing their marginal costs. For instance, De Ridder (2021) documents that intangibles reduce marginal costs and raise fixed costs, therefore affecting firm market power and economic growth.[11] In Appendix Table B.13, we proxy bank efficiency and profitability using alternative measures such as cost-to-income ratio, income-over-asset, and profit-over-asset. The results are consistent with those in our baseline analysis: bank innovation significantly decreases the cost-to-income ratio (enhancing the operating efficiency) and increases profit-over-asset and income-over-asset (improving profitability).

2.3.2 Effects of banking innovation on bank risk-taking

Besides cost reduction, banking innovation may affect banks' risk-taking behaviors in opposite ways. Innovation decreases the marginal cost of producing a loan and facilitates loan lending, resulting in more loan lending. Such technological innovation enables banks to lend to the marginal borrower, therefore investing in more risky assets and introducing potentially unknown risks.[12] On the other hand, banking innovation can improve a bank's ability to pro-

[11] We are unable to distinguish bank fixed costs further because there are only limited numbers of Chinese commercial banks that report expenses on depreciation and amortization of fixed assets, which partly covers expenses on-premises and fixed assets.

[12] The risk-shifting channel could work as follows. First, banks that adopt new technologies (e.g., artificial intelligence, blockchain, cloud computing, data analytics), may be able to improve their operating efficiency. Such a positive cost-reducing effect allows banks to shift and allocate more funds from investments in innovation into risky loan lending since the latter yields a higher return. For example, banking innovation may improve risk management efficiency so that banks may reach the same monitoring level by exerting less effort. Thus, banks can allocate more funds to risky loans by lending to more potentially marginal borrowers. Second, technological innovation or IT adoption allows banks to expand their power to new lending markets and offer innovative

Table 3: Effects of Banking Innovation on Bank's Risk-taking

	Non-performing Loans Ratio			Risk-weighted Assets Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation$_{i,t-1}$	0.189***	0.678***	0.843***	0.210***	0.141***	0.010
	(0.021)	(0.221)	(0.319)	(0.009)	(0.014)	(0.020)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-
Time FEs	-	-	Yes	-	-	Yes
$\mathbf{R}^2$	0.526	0.533	0.578	0.616	0.628	0.679
Observations	1553	1337	1337	1580	1580	1580

NOTE: This table presents the results of regressing bank risk-taking measures on banking innovation. Bank-level controls, bank- and year-fixed effects, and aggregate-level controls are specified when indicated. Columns (1)-(3) show the results for ex-post risk-taking measured by non-performing loan ratios. Columns (4)-(6) show the results for ex-ante risk-taking measured by risk-weighted assets share as a robustness test. Numbers in the parentheses indicate robust standard errors. Asterisks denote levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

cess information and monitor borrowers more effectively and efficiently, therefore mitigating risk-taking. However, it remains insufficiently studied in existing research for how banking innovation could affect bank risk-taking.

In this section, we empirically document the impacts of banking innovation on risk-taking by using a similar estimation strategy as before. We consider the non-performing-loan ratio and the share of risk-weighted assets as two measures of bank risk-taking. These two indicators correspond to the ex-post and ex-ante proxies of bank risk-taking.

Table 3 reports the main results. Columns (1) to (3) and Columns (4) to (6) correspond to the results for cases of non-performing loan ratios and risk-weighted assets, respectively. The results suggest that bank innovation significantly increases bank risk-taking. For instance, Columns (1) and (4) indicate that a one percentage increase in the level of banking innovation significantly increases its non-performing loan ratio by 0.189% and increases a bank's risk-weighted asset share by 0.210%, respectively. The positive effects on bank risk-taking remain robust when aggregate controls or time-fixed effects are considered.

loan products, which substantially increases credit risks. Moreover, our measurement of banking innovation also includes the possibilities of banks' IT adoption and banks' cooperation innovation projects, such as alternative lending platforms. Such loan origination products leverage banks' technological capabilities and often serve riskier borrowers or facilitate loans with less stringent credit criteria if no regulations exist.

2.4 Robustness Analysis

We next conduct a battery of robustness checks. Firstly, we validate the cost-reducing channel by focusing on marginal non-interest net expenses. We report our results in Table 4.

Table 4: Effects of Banking Innovation on Marginal Non-interest Net Expenses

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Innovation$_{i,t-1}$	-0.351*** (0.026)	-0.182*** (0.040)	-0.102* (0.060)	-0.491*** (0.033)	-0.591*** (0.087)	-2.909** (1.480)
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-
Time FEs	-	-	Yes	-	-	Yes
$\mathbf{R}^2$	0.627	0.637	0.752	-	-	-
Observations	1580	1580	1580	1580	1580	1580

NOTE: This table reports the estimated results of regressing marginal non-interest net expenses on banking innovation. Bank-level controls, bank- and year-fixed effects, and aggregate-level controls are specified when indicated. Columns (1)-(3) show the results of the OLS estimation. Columns (4)-(6) show the results of the 2SLS IV estimation. Numbers in parentheses indicate robust standard errors. Asterisks denote levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Column (1) runs an OLS estimation without aggregate controls and time-fixed effects. Column (2) adds aggregate controls, and Column (3) alternatively adds time-fixed effects. Columns (4)-(6) report counterpart results in the IV regressions. The IV regressions in Columns (4) to (6) deliver similar results, but the coefficients are higher than those of our baseline estimates.[13] The first-stage regression and identification test results are reported in Table B.4 in the Appendix. The p-values for Kleibergen-Paap rk LM statistics are all close to zero, which rejects the null hypothesis of the weak IV identification test, indicating that our choice of instrument variables is reasonable.

We re-estimate Table 2 and Table 3 using 2SLS with the constructed instrument variable. The corresponding results are shown in Tables B.5 and B.6 in the Appendix. The signs of the coefficients are consistent with our original estimations at a significant level. Also, the IV estimates

[13]Two possible reasons can explain larger estimates. First, endogeneity issues may cause the OLS estimates to underestimate the effect. For example, banks with a higher share of graduate employees indicate a higher average education level and a higher level of IT employees. These banks may benefit more from investment in innovation, indicating a larger cost reduction and improved performance. Although we include time-varying local economic variables to address this issue, unaddressed biases may still exist. Second, banking innovation may promote performance and efficiency more easily when labor market frictions in high-tech fields decrease because of larger increases in the availability of domestic talent.

are relatively larger than OLS coefficients since our instruments correct for measurement errors in the data with respect to bank-level innovation that does not arise at the national level.

For the analysis that we have described in this section, we measure overall banking innovation by including applications and practices of existing technologies. We now focus on only in-house innovation to conduct the robustness analysis. To do so, we follow the literature of patent-based technological innovation (e.g., Chen et al. (2019), Jiang et al. (2022c), Hasan et al. (2023)), and classify bank patent applications based on the International Patent Classification (IPC) codes. The remaining patent applications in our sample mostly belong to G06Q. Specifically, this code pertains to data processing systems and technological methods primarily tailored for administrative, commercial, financial, managerial, supervisory, or forecasting purposes. Notably, within the G06Q category, the most prevalent subcategories observed in our sample are G06Q20, G06Q30, and G06Q40. These specific IPC codes encompass digital innovations used in payment systems, e-commerce platforms, and financial services, and constitute a broad range of FinTech applications used in the banking sector (see Chen et al., 2019).

Results in Table 5 show that the patent-based measurement of banking innovation still significantly reduces bank marginal net expenses under both OLS and 2SLS estimates. Column (3) indicates that an increase in patent-based innovations is associated with a 0.052% reduction of marginal net costs. The magnitudes are smaller than the results in Table 4 since the patent-based measurement of banking innovation narrows the coverage of various bank technological investments and uses of new services and platforms to the classification of in-house technological innovation.

We replicate the results in Table 2 and Table 3 using the patent-based measurement of banking innovation. The estimation further validates our primary findings, as shown in Tables B.7 and B.8 in the Appendix.

Our baseline estimation results are also robust to alternative measurement construction and model specifications. Firstly, we construct the measure of banking innovation based on perpetual inventory methods, which reflects the overall level of innovations. In Tables B.9 and B.10 in the Appendix, we use the growth of this measurement to capture gross investments in innovation ($\Delta \text{Innovation}_{i,t-1}$). The results show that one unit of additional investment in banking innovation significantly contributes to a decrease in marginal net expenses, resulting in a higher markup on loans. Moreover, a higher amount of newly installed investment in innovation is associated with a higher level of risk-taking, which is proxied by the non-performing loans ratio and the risk-weighted assets share.

The construction of such a measurement relies on capitalizing a fraction of general administrative expenses. Some may argue that, compared to other developed countries, there could be a larger part of general administrative expenses unrelated to employee training and potential efforts on innovative investment. This originates from either inefficient operations or concerns

Table 5: Cost-reducing Channel: Patent-based Innovation

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Innovation$_{i,t-1}$	-0.248***	-0.110***	-0.052*	-0.526***	-0.350***	-0.193***
	(0.025)	(0.027)	(0.029)	(0.037)	(0.051)	(0.056)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-
Time FEs	-	-	Yes	-	-	Yes
$\mathbf{R}^2$	0.603	0.634	0.751	0.567	0.613	0.681
Observations	1589	1589	1589	1589	1589	1589

NOTE: This table presents the results of regressing marginal net expenses on the patent-based measurement of banking innovation. Bank-level controls, bank and year-fixed effects, and aggregate-level controls are specified when indicated. Column (1)-(3) show the estimation results using OLS, and column (4)-(6) show the results using 2SLS with instrument variables described before. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

that Chinese commercial banks cannot translate technological expenses into productivity as much as possible. To reconcile this issue, we reconstruct our measurement by only capitalizing 5% of general administrative expenses. The estimation results shown in Tables B.11 and B.12 in the Appendix evidently support our main conclusions.

Finally, we check other performance and efficiency measures that are often used in the empirical banking literature, such as cost-to-income ratio, income-over-asset ratio, and profit-over-asset ratio (Bikker and Haaf, 2002, Lin and Zhang, 2009). The results in Table B.13 in the Appendix suggest that a higher initial level of banking innovation is associated with a higher income-over-asset ratio and profit-over-asset ratio, and a larger reduction on cost-to-income ratio. Therefore, overall banking innovation could help banks operate more efficiently and do so with a relatively large cost reduction.

Since Chinese commercial banks exhibit striking heterogeneous features, we investigate which type of banks benefit the most from innovation in reducing marginal net expenses. Table B.14 in the Appendix indicates that banks with lower risk exposure, of larger size (especially top 5 banks, which are state banks), and with higher profit benefit the most from investing in innovation to reduce their non-interest costs, thus leading to a positive correlation between innovation investment efficiency and bank profitability and size.

To summarize, our empirical analysis suggests that banks reduce marginal non-interest-related net expenses and enhance their performance and efficiency by investing in innovation.

Large and state banks benefit the most from innovation through this cost-reducing channel. As an unintended consequence, banking innovation increases risk-taking as banks' non-performing loans ratios and risk-weighted assets shares significantly increase.

Building on our empirical analysis, in the next section we further explore the mechanisms through which innovative investment decisions may endogenously affect other investment activities (e.g., risk-taking behaviors) within banks. Furthermore, the implications of such investment decisions on social welfare in a general equilibrium remain unclear in the literature, especially considering the heterogeneity of banks' innovation efficiency.

3 Model

Motivated by our empirical findings, we construct a structural general equilibrium model to investigate the aggregate impacts of banking innovations. We further study the welfare implications when individual banks' innovative investment and lending activities are affected by changes in banking technologies. The model features heterogeneous banks and the general equilibrium feedback when individual banks face government regulations. For transparency and clarity, we consider a two-period model. Time is denoted as $t = \{0, 1\}$. The economy is populated by households, banks, and firms.

There is a continuum of banks with a unit measure. Banks absorb deposits from households and make loans to firms in $t = 0$. There are two types of firms: one with safe technology and one with risky technology. Each firm borrows from banks through bank loans. Lending to safe/risky firms produces safe/risky loans. The bank decides the portfolio for these two types of loans. We assume a monopolistic risky loan market and a competitive safe loan market. As a result, the bank can influence its price for risky firms, resulting in differential loan rates; while for the safe loan market, there is a homogeneous loan rate across borrowers. We assume the bank takes limited liability for a household deposit when facing bankruptcy. The household deposit is insured by the deposit insurance. Besides loan assets, each bank can choose to invest in innovative technology. The innovative investment helps baks reduce non-interest costs in the next period if the innovation is successful. The non-interest cost corresponds to the marginal non-interest net expense in our empirical analysis and includes the monitoring costs and fixed operating costs in the quantitative model. To further introduce the model details, we start with the household sector.

3.1 Households

A representative household lives for two periods. She is risk neutral with linear preferences in consumption, $C_0 + \beta C_1$, where $\beta \in (0, 1)$ is the discount factor. The representative household owns all firms and banks in the economy, and the profits and dividends are distributed to households for consumption. There are also no financial frictions for the households. They face a competitive deposit market and are indifferent among deposits offered by heterogeneous banks. This implies that $\beta(1+r) = 1$, where r is the exogenous deposit rate in the deposit market.

3.2 Firms

Following the standard banking literature, we assume there are two types of firms: safe technology (S) and risky technology (R). Within each type of firm, there is a representative firm with a unity measure. All firms use bank loans to finance their production capital at $t = 0$.

A firm with safe technology obtains l^S units of the loan at $t = 0$. In the next period, it can obtain revenues (net of all other expenses) as $\left(1 + A^S\right) f(l^S)$, where $f(\cdot)$ is strictly increasing and concave in l^S, with $f'(\cdot) > 0$ and $f''(\cdot) < 0$; A^S characterizes the quality of the project, which is a constant. We denote p^S as the loan price for a safe project that must be repaid to banks in the second period. The firm chooses the amount of loan l^S to maximize its profit $(1 + A^S)f(l^S) - (1 + p^S)l^S$. The firm's loan demand is then given as follows:

$$\left(1 + A^S\right) f'(l^S) = 1 + p^S. \tag{2}$$

In the special case of $f'(l^S) = 1$, one unit of loan can bring in a gross return of $1 + A^S$ and the market price for a safe loan is $p^S = A^S$.

A firm with risky technology demands a composite loan l^R that combines loans, $l^R(j)$, from a continuum of heterogeneous banks through a CES aggregation technology,

$$l^R = \left[\int_{j=0}^{1} l^R(j)^{\frac{\epsilon-1}{\epsilon}} dj \right]^{\frac{\epsilon}{\epsilon-1}}, \tag{3}$$

where $\epsilon > 1$. The market for $l^R(j)$ is monopolistic competition. The loan price set by an individual bank j is $p^R(j)$. It is straightforward to show that the demand for individual loan $l^R(j)$ satisfies:

$$\frac{p^R(j)}{p^R} = \left[\frac{l^R(j)}{l^R} \right]^{-\frac{1}{\epsilon}}. \tag{4}$$

The price of the composite loan is p^R, satisfying the indexation equation:

$$p^R = \left[\int_{j=0}^{1} p^R(j)^{1-\epsilon} dj \right]^{1/(1-\epsilon)}. \tag{5}$$

With probability $\chi \in (0,1)$, the project is successful with a revenue of $\left(1 + A^R\right) f(l^R)$. With probability $1 - \chi$, the risky project will fail with zero revenue. We assume that the expected rate of return $\chi \left(1 + A^R\right)$ is sufficiently large, satisfying $\chi \left(1 + A^R\right) > 1 + A^S$, such that the risky technology earns a higher return for any given level of loans without financial frictions. The firm's expected profit is given by $\chi \left[\left(1 + A^R\right) f(l^R) - \left(1 + p^R\right) l^R\right]$. Similarly, the composite loan demand for the risky firm satisfies the optimal condition:

$$\left(1 + A^R\right) f'(l^R) = 1 + p^R. \tag{6}$$

This model setup implicitly assumes that banks can diversify idiosyncratic firm-level shocks; however, the failure risk cannot be diversified.

We assume a monopolistic competition market for risky loans and a competitive market for safe loans for the sake of simplicity. Doing so implies that the risk-free rate is the same across different banks, and the risky loan rates charged by individual banks vary across banks.[14] The bank competition environment in our model departs from those in Boyd and De Nicolo (2005) and Martinez-Miera and Repullo (2010). These two papers focus on a symmetric Cournot equilibrium for bank competition, in which banks compete over the amount of loans. Instead, we allow for both price and quantity competition in a relatively parsimonious framework. As a result, we can flexibly account for heterogeneous bank sizes, differential banking innovation decisions, and differential impacts of bank regulations, among others. As we will see later, because individual banks' optimal decisions will influence the aggregate supply side of the loan market, the price and quantity of loans are endogenous in the general equilibrium. When regulation and aggregate economic conditions change, loan prices and quantities will be affected. Theoretical research (e.g., Martinez-Miera and Repullo (2010)) also suggests that considering equilibrium project performance and loan performance may have important implications for banks' competition and risk-taking decisions.[15]

[14]One could motivate the assumption by the fact that risk-free return rates have quite limited variations in the presence of other risk-free investment opportunities in the data. For instance, with the existence of government treasury, international bonds, and so on, no arbitrage implies that risk-free return rates are almost the same across banks.

[15]The framework is also feasible for more extensions. We could also allow for more general market structures in the loan markets, such as Klenow and Willis (2016), where price elasticity and markups depend on market share (larger firms could charge even higher markups). In this way, we do not need to model the endogenous market structure and banks' dynamics explicitly; see Corbae and D'Erasmo (2021) for details along these lines.

3.3 Bank

Banks live for two periods and are owned by the representative household. Each individual bank is indexed by $j \in (0, 1)$. Bank j is endowed with initial capital, $e(j)$, and receives $b(j)$ amount of deposit. For the sake of simplicity, we assume $b(j)$ is randomly drawn from a particular distribution. The bank makes investment decisions in the first period, including loan portfolio and innovation decisions. The bank's innovative investment in the model is banking-related R&D investment, which helps reduce non-interest expenses/costs. In the second period, investment outcomes are realized, and the cost takes place. The bank either distributes the profit to the households if it obtains a positive profit, or the bank takes limited liability if it is bankrupt. In the latter case, deposit insurance is implemented. We start by introducing the bank's optimization problem.

3.3.1 Bank's optimization problem

Let $i(j)$ denote R&D investment of bank j. The budget constraint facing the bank in the first period is

$$l^S(j) + l^R(j) + i(j) = e(j) + b(j), \tag{7}$$

where loan allocations to safe and risky projects and R&D investment are non-negative, i.e., $l^S(j) \geq 0$, $l^R(j) \geq 0$, and $i(j) \geq 0$. This setting implicitly assumes that the bank can only obtain external finance through deposits.

The bank's cost structure consists of interest-related costs and non-interest expenses. The interest-related cost for loans is $(1 + r)b(j)$, and $(1 + p^S)l^S(j) + [1 + p^R(j)]l^R(j)$ is the loan revenue. Notice that the price of risky loan $p^R(j)$ is bank-specific as the bank has pricing power on its risky loans. The non-interest expenses include the loan issuance cost that is proportional to the total amount of loans $c_L[1 - z(j)] \left[l^S(j) + l^R(j)\right]$ and the fixed operation cost $c_F[1 - z(j)]$. Here, $c_L[1 - z(j)]$ is the coefficient for the loan issuance cost, where $z(j)$ is the innovation rate that is strictly increasing in the bank's R&D investment, and $c_L > 0$ denotes the monitoring cost per unit of loan as in Diamond (1984) and Philippon (2010); $c_F > 0$ is the cost parameter corresponding to the fixed operation cost. Innovation rate $z(j)$ is the outcome of R&D investment $i(j)$ that satisfies:

$$i(j) = [e(j) + b(j)] \frac{1}{\omega} z(j)^\eta, \tag{8}$$

where $\eta > 1$, and $\omega > 0$ captures the efficiency of R&D investment. The above function indicates the R&D cost is convex and proportional to the bank's total size of asset $e(j) + b(j)$. This function reflects the idea that to achieve bank-wide innovation rate $z(j)$, larger banks must invest more in levels.[16] The elasticity of innovation rate $z(j)$ with respect to the investment rate, $\frac{i(j)}{e(j)+b(j)}$, is

[16]The cost structure is similar to those in the literature (e.g., Klette and Kortum (2004), Acemoglu et al. (2018),

given by $1/\eta$. The cost function (8) is also consistent with the previous empirical finding that R&D investment reduces marginal non-interest net expenses. That is, under an innovation rate of z, the loan issuance unit cost c_L is reduced to $c_L(1-z)$, and the fixed operation cost c_F is reduced to $c_F(1-z)$.

In the second period, the bank obtains profit $\pi(j)$, which is random and depends on the realized outcome of loan allocations. In particular, with the probability of χ, the risky project succeeds, and the risky loan is repaid. With the probability of $1-\chi$, the risky project fails, and the loan defaults.

In the case of not default, the bank profit is given by:

$$\pi(j) = (1+p^S)l^S(j) + [1+p^R(j)]l^R(j) - \sum_{\iota=\{S,R\}} c_L[1-z(j)]l^\iota(j) - c_F[1-z(j)] - (1+r)b(j). \quad (9)$$

When the loan defaults, the bank's profit is:

$$\pi(j) = (1+p^S)l^S(j) - \sum_{\iota=\{S,R\}} c_L[1-z(j)]l^\iota(j) - c_F[1-z(j)] - (1+r)b(j). \quad (10)$$

Banks take limited liability. When the profit is negative, the bank receives a transfer from the government to pay off the relevant costs. In this case, the bank has zero profits, and the transfer is financed by lump-sum taxes imposed on households (we provide more details later in the welfare analysis).

The limited liability encourages the bank's risk-taking behaviors. To characterize the policy regulation on the bank's risk-taking, we further introduce a capital adequacy ratio (CAR) constraint satisfying:

$$\frac{e(j)}{l^S(j) + \psi l^R(j)} \geq \xi, \quad (11)$$

where $\psi > 1$ is the weight on risky assets, and the term $l^S(j) + \psi l^R(j)$ is the bank's risk-weighted assets, parameter $\xi > 0$ is the required weight of risky loans in the CAR regulated by the government.

The bank's optimization problem is to choose loan portfolios $\{l^S(j), l^R(j)\}$, R&D investment $i(j)$ and loan price $p^R(j)$ to maximize the expected value $\mathbb{E}[\max\{\pi(j), 0\}]$. The expectation operator $\mathbb{E}$ is taken on the random outcome of whether the risky project succeeds or not. The bank faces the budget constraint (7), the CAR constraint (11), and non-negative constraints for portfolio and investment decisions: $l^S(j) \geq 0, l^R(j) \geq 0, i(j) \geq 0$.

The bank's optimization problem is essentially a constrained, multi-dimensional portfolio choice and R&D investment problem. As the bank's profit $\pi(j)$ is state-dependent, we

Akcigit and Kerr (2018)).

must have $\pi(j) > 0$ when the risky project succeeds; otherwise, the bank's expected value, $\mathbb{E}\left[\max\left\{\pi(j), 0\right\}\right]$, cannot be positive. Since banks are heterogeneous in the initial equity $e(j)$ and deposit $b(j)$, the bank may not necessarily go into bankruptcy even if the risky loan defaults. For instance, a bank with sufficiently large initial equity and low deposits may still earn positive profit from the safe loan when the risky project fails. Only a negative profit $\pi(j) < 0$ conditional on the failure of the risky project leads to bankruptcy (insolvency). Let $\mathbf{I}\left(j\right)$ denote the indicator for the event of bankruptcy, equal to 1 if the bank does not go bankrupt and zero for insolvency. It is straightforward that the indicator $\mathbf{I}\left(j\right)$ depends on the individual bank's state. We can rewrite the bank's expected value as:

$$\mathbb{E}\left[\max\left\{\pi(j), 0\right\}\right] = \left[\chi + (1-\chi)\mathbf{I}\left(j\right)\right]\pi(j). \tag{12}$$

3.3.2 Bank's optimal decisions

We now characterize the bank's optimal decisions for loan portfolios $\left\{l^S\left(j\right), l^R\left(j\right)\right\}$ and R&D investment $i\left(j\right)$. Given the firm's demand for risky loans, the bank simultaneously determines the price, $p^R\left(j\right)$, and the quantity of risky loans, $l^R\left(j\right)$. The expected profit $\mathbb{E}\left[\max\left\{\pi(j), 0\right\}\right] = \left[\chi + (1-\chi)\mathbf{I}\left(j\right)\right]\pi(j)$ is piece-wise, relying on the bank's solvency or the value of $\mathbf{I}\left(j\right)$.

Let $\lambda\left(j\right)$ and $\phi\left(j\right)$ denote the Lagrangian multipliers for the budget constraint (7) and the CAR constraint (11), respectively. The optimal condition for R&D investment $i\left(j\right)$ satisfies:

$$\lambda\left(j\right) = \beta\left[\chi + (1-\chi)\mathbf{I}\left(j\right)\right]\left\{c_L\left[l^S(j) + l^R\left(j\right)\right] + c_F\right\}\frac{\partial z(j)}{\partial i\left(j\right)}, \tag{13}$$

where $\frac{\partial z(j)}{\partial i(j)} = \frac{z(j)}{\eta i(j)}$.

The left-hand side (L.H.S.) of the last equation is the marginal cost of investing in one unit of R&D capital. The right-hand side (R.H.S.) indicates the expected marginal benefit in the sense that one unit of R&D investment increases the innovation rate $z\left(j\right)$ by $\frac{\partial z(j)}{\partial i(j)}$, which further helps reduce the non-interest expenses of $c_L\left[l^S(j) + l^R\left(j\right)\right] + c_F$. The expected reduction in non-interest expenses depends on the state of the risky project, which is characterized by $\chi + (1-\chi)\mathbf{I}\left(j\right)$.

The optimal condition for the safe loan $l^S\left(j\right)$ is given by:

$$\lambda\left(j\right) + \phi\left(j\right)\xi = \beta\left\{1 + p^S - c_L[1 - z(j)]\right\}\left[\chi + (1-\chi)\mathbf{I}\left(j\right)\right]. \tag{14}$$

The L.H.S. reflects the marginal cost of allocating safe loans, in which the term $\phi\left(j\right)\xi$ reflects the extra shadow price of safe loans due to the regulation of the capital requirement. The R.H.S. indicates the marginal benefit for allocating safe loans, which is the difference between the expected interest income and the expected non-interest expenses induced. Similarly, the optimal condition for the risky loan $l^R(j)$ satisfies:

$$\lambda(j) + \phi(j)\,\xi\psi = \beta\chi\left[1 + \frac{\epsilon - 1}{\epsilon} p^R(j)\right] - \beta\left[\chi + (1-\chi)\mathbf{I}(j)\right] c_L[1 - z(j)]. \tag{15}$$

From the last two optimal conditions, we can derive the price dispersion between the risky loan and the safe loan:

$$p^R(j) - p^S = \frac{1}{\epsilon - 1} p^S + \frac{1}{\beta\chi}\frac{\epsilon}{\epsilon - 1}\phi(j)\,\xi(\psi - 1) + \frac{1}{\chi}\frac{\epsilon}{\epsilon - 1}(1 + p^S)(1-\chi)\mathbf{I}(j). \tag{16}$$

The premium of a risky loan consists of three components. The first term $\frac{1}{\epsilon-1}p^S$ reflects the bank's market power on the risky loan market, compared to the competitive market of safe loans. The second term $\frac{1}{\beta\chi}\frac{\epsilon}{\epsilon-1}\phi(j)\,\xi(\psi-1)$ reflects the extra cost of holding risky loans because of the regulation of capital requirement ($\psi > 1$). This is because a risky loan bears a larger risk weight that may tighten the CAR constraint. If the CAR constraint does not bind ($\phi(j) = 0$) or if the risky loan shares a same risk-weight ($\psi = 1$), the second premium term vanishes. The third term $\frac{1}{\chi}\frac{\epsilon}{\epsilon-1}\left(1 + p^S\right)(1-\chi)\mathbf{I}(j)$ reflects the risk premium because the risky loan may induce bankruptcy.

In a special case in which the CAR constraint is not binding ($\phi(j) = 0$), no events of bankruptcy emerge ($\mathbf{I}(j) = 1$) and $\beta = 1$, and the safe loan decision implies:

$$\lambda(j) + c_L[1 - z(j)] = 1 + p^S, \tag{17}$$

and the optimal condition for the risky loan implies that the price for the risky loan is homogeneous across banks,

$$p^R(j) = p^R = \frac{1}{\chi}\frac{\epsilon}{\epsilon - 1}\left(1 + p^S\right). \tag{18}$$

The risky loan's price premium merely reflects the risk cost and the bank's market power. In this special case, the optimal condition for the bank's R&D investment can be expressed as:

$$\begin{aligned} 1 + p^S &= \left\{c_L\left[l^S(j) + l^R(j)\right] + c_F\right\}\frac{\partial z(j)}{\partial i(j)} + c_L[1 - z(j)] \\ &= \frac{\omega}{\eta}\left\{c_L\left[1 - \frac{1}{\omega} z(j)^{\eta}\right] + \frac{c_F}{e(j) + b(j)}\right\} z(j)^{1-\eta} + c_L[1 - z(j)], \end{aligned} \tag{19}$$

where $\frac{\partial z(j)}{\partial i(j)} = \frac{z(j)}{\eta i(j)}$. The second equality is obtained by using (7), (8), and (17). The last equation indicates that the optimal R&D investment strictly increases with innovation efficiency ω and the coefficients of non-interest cost c_L and c_F. In addition, a higher loan price p^S dampens the bank's R&D investment because of substitution effects.

When the CAR constraint becomes effective, $\phi(j) > 0$, a tightening of the CAR constraint implies $\phi(j)$ increases. (16) indicates that compared to the case without CAR constraint, the bank raises the price of risky loans, reducing the supply of risky loans. This is because the CAR constraint is risk-sensitive, allocating more risky loans may increase the bank's risk-weighted assets, resulting in a tightened CAR constraint. Thus, facing a tightened CAR constraint, the bank tends to allocate less risky loans despite a higher return on such loans. This risk-return trade-off channel provides a crucial mechanism to explain a positive relationship between the bank's innovation investment and risk-taking observed in our empirical analysis. A larger innovation investment crowds out the bank's total loan supply, $l^R(j) + l^S(j)$, and loosens the CAR constraint ($\phi(j)$ declines). As a result, the bank can take more risks by allocating more risky loans.

3.4 General Equilibrium and Social Welfare

General equilibrium We define the aggregate safe loans as $l^S = \int_0^1 l^S(j)\,dj$. The initial distribution for an individual bank's equity and deposit $\{e(j), b(j)\}$ are exogenously given. We define the total initial asset, $\bar{a}$, as the sum of initial equity and deposits, i.e., $\bar{a} = \int_{j=0}^{1} [e(j) + b(j)]\,dj$. In the numerical exercises later on, we scale total output, social welfare, and other measures by $\bar{a}$.

The demand for safe loans is determined by (2). The supply of safe loans is given by (17). For risky loans, the price and quantity of composite loan, $\{p^R, l^R\}$, are determined by the price indexation equation (5) and demand equation (6). The price and quantity of individual risky loans $\{p^R(j), l^R(j)\}$ are determined by individual banks in the monopolistic risky loan market.

In the equilibrium, the representative household's wealth in the second period ($t = 1$) consists of the total profits of banks, $\int_{j=0}^{1} \mathbb{E}\max\{\pi(j), 0\}\,dj$, and total profits of firms, $\pi_f^S + \pi_f^R$, and all repayments of the financial assets in the second period, $(1+r)\int_{j=0}^{1} b(j)dj$. In addition, for those insolvent banks that have negative profits, there will be government transfers from households to banks through deposit insurance with a total amount of $\int_{j=0}^{1} (1-\sigma)\,\mathbb{E}\min\{\pi(j), 0\}\,dj$. The parameter $\sigma \in (0,1)$ captures the dead-weight loss of the government transfer, which reflects the social costs of moral hazard for banks (Hellmann et al., 2000). The household then consumes all of her income in the second period as C_1. Without loss of generality, we normalize the income and the consumption in the first period to be zero.

Social welfare The social welfare W can be computed as βC_1. According to the previous analysis, social welfare can be written as:

$$W = \beta \mathbb{E} \int_{j=0}^{1} \pi(j) dj + \beta(\pi_f^S + \pi_f^R) + \beta(1+r) \int_{j=0}^{1} b(j) dj - \sigma\beta\mathbb{E} \int_{j=0}^{1} \min\{\pi(j), 0\} dj, \qquad (20)$$

where we use the relationship $\int_{j=0}^{1} \pi(j)dj = \int_{j=0}^{1} \max\{\pi(j), 0\} dj + \int_{j=0}^{1} \min\{\pi(j), 0\} dj$. We can further express the total welfare as:

$$W = \beta \sum_{\iota=\{S,R\}} \mathbb{E}\left[f(l^\iota)\right] - \beta \int_{j=0}^{1} \left\{ \sum_{\iota=\{S,R\}} l^\iota(j) c_L \left[1 - z(j)\right] + c_F \left[1 - z(j)\right] - \sigma \mathbb{E} \min\{\pi(j), 0\} \right\} dj. \qquad (21)$$

The social welfare essentially equals the total expected output net of different types of costs in the banking sector. It is straightforward that an increase in the bank's $z(j)$ for $j \in (0,1)$ may improve social welfare because of the cost reduction.

4 Calibration and Model Fits

Preceding to the quantitative analysis, we set values for our model parameters. For standard parameters, we directly set their values according to those in the literature. For the remaining model-specific parameters, we calibrate their values using the simulated method of moments (SMM). One period in the model corresponds to one year, consistent with the empirical data.

We set the risk-free deposit rate, r, to be 0.021, the value observed in our data set. Since the representative household is risk-neutral, we calibrate the discount rate β through the relationship $\beta = 1/(1+r) = 0.9794$. For the firm's production function, we assume that the safe technology is a constant return to scale, i.e., $f^S(l) = l$. For risky technology, we assume it is strictly concave, following $f^R(l) = l^\alpha$, where α is set to be 0.5, such that the scale of return is a simple average of those for capital and labor (e.g., the average of 0.64 and 0.36). For technology parameters, A^S and A^R, since there are no direct empirical measures, we follow Song et al. (2011) and proxy them by using the average rate of returns to capital investment across state-owned firms and privately-owned firms, resulting in $A^S = 5\%$ and $A^R = 14\%$.[17] The parameter η governs the elasticity of innovation rate for successful projects to R&D investment. To the best of our knowledge, there are few direct measures in the literature, and we do not have good empirical

[17]The value of 14% is also close to China's unsecured credit card interest rates. See the data from www.Bankrate.com and the report from Bloomberg.

counterparts in our context either. Thus, we borrow estimates from Acemoglu et al. (2018), Akcigit and Kerr (2018) and Aghion et al. (2021), and set η to be 2.5.

For ξ, the regulated Capital Adequacy Ratio in the CAR constraint, we set it to 12%, consistent with the average CAR observed in the data.[18] For the risk-weight parameter ψ in the CAR constraint, we set it to be 1.50. This calibration value is based on the annual reports of the "Big Five" banks.[19] A value of 1.50 for ψ indicates that one unit of risky loan in the model would be weighted with 50% more risks compared to the safe loan.

We set σ to be 0.20, implying an additional 20% deadweight loss for the whole society if there are bank bailouts. This value is relatively conservative compared to the real events discussed in Hellmann et al. (2000). We experiment with different values in the following exercises as sensitivity analysis.

For the remaining model-specific parameters, we use a simulated method of moments (SMM) approach to calibrate their values. In particular, we calibrate the joint distribution of the initial equity $e(j)$ and the leverage $L(j) \equiv \frac{e(j))}{e(j)+b(j)}$ to pin down the joint distribution of $e(j)$ and $b(j)$. We specify that their logs follow a joint-normal distribution:

$$\begin{aligned} \log(e(j)) &\sim \mathcal{N}(1, \sigma_e^2), \\ \log(L(j)) &= \rho_{e,L} \log(e(j)) + \mathcal{N}(\mu_L, \sigma_L^2). \end{aligned}$$

For the initial distribution of ω, we assume that its logarithm follows:

$$\log(\omega) = \rho_{e,\omega} \log(e(j)) + \mathcal{N}(\mu_\omega, \sigma_\omega^2).$$

Given this specification, we have seven parameters regarding the initial distributions, $\{\sigma_e, \sigma_L, \sigma_\omega, \rho_{e,L}, \rho_{e,\omega}, \mu_L, \mu_\omega\}$, need to be pinned down. In addition, we need to estimate ϵ, the loan demand elasticity, χ, the probability of project succeed, m, the non-interest marginal cost per loan, and c_F, the non-interest fixed cost coefficient.

We choose a rich set of relevant model moments and data moments to best estimate the parameters. Intuitively, for the parameters related to the initial distributions, the following moments can provide closely related information for $e(j)$ and $b(j)$: the standard deviations for log equity and for log assets, the average and standard deviation for banks' leverage, and the correlation between equity and bank leverage. For $e(j)$ and ω, the correlation between R&D investment and bank equity, the average and the standard deviation of R&D investment (scaled by bank revenue), can provide close information on $\rho_{e,\omega}$, μ_ω, and σ_ω. For ϵ, c_L, and c_F, they affect the model's implied markup of marginal prices over marginal costs across different banks,

[18] For the so-called "Big Five" banks, Li et al. (2022) shows the average CAR is above 12%.

[19] These banks are required to disclose their internal assessments of CAR, procedures, and risk weighting for different types of assets.

Table 6: Endogenously Estimated Parameters

Parameter	Description	Value
χ	Prob. of Project Succeed	0.898
c_L	Non-interest Cost per Loan	0.017
c_F	Non-interest Fixed Cost	0.355
σ_e	Std. for $\log(e(j))$	1.415
$\rho_{e,L}$	Corr. between $\log(e(j))$ and Leverage	-0.253
μ_L	Mean in $\mathcal{N}(\mu_L, \sigma_L^2)$	-2.170
σ_L	Std. in $\mathcal{N}(\mu_L, \sigma_L^2)$	0.427
$\rho_{e,\omega}$	Corr. between $\log(e(j))$ and $\log(\omega)$	1.132
μ_ω	Mean in $\mathcal{N}(\mu_\omega, \sigma_\omega^2)$	2.541
σ_ω	Std. in $\mathcal{N}(\mu_\omega, \sigma_\omega^2)$	0.206

the average and dispersion of revenue/assets, and also the correlation between bank size and total cost/total revenue. For χ, the moments on banks' risky shares and CAR can provide more relevant information.[20]

All of these parameters are simultaneously determined in SMM. We use an identity matrix for 19 moments to estimate the above 11 parameters. Table 6 lists the parameter values, and Table 7 compares the model and data moments in detail. Our model can fit the data reasonably well across the rich set of moments. Given that our model structure is deliberately kept transparent and relatively parsimonious, we believe that our framework offers a good first step for modeling and studying Chinese banks.

5 Quantitative Exercises

In this section, we leverage our quantitative model and further explore the implications when banks endogenously choose optimal innovation activities. In particular, we aim to document how banks' other investment activities (i.e., risky taking behaviors) are also endogenously affected and, consequently, the implications on banks' bankruptcy probability, social deadweight loss, and total social welfare.

5.1 Characterizing innovation activities

Who innovates? In Figure 3, we first examine innovation activities across different banks. We divide banks into five quintiles based on their innovation efficiency, ω. For each group, we

[20] Markup in the model is computed as total expected payments over total expected total variable cost: $\frac{\mathbb{E}_\chi\left[l^S(j)(1+p^S)+l^R(j)(1+p^R(j))\right]}{b(j)r+\mathbb{E}_\chi\left[l^S(j)+l^R(j)\right]c_L(1-z(j))} - 1$, which is defined as close to the empirical counterpart as possible.

Table 7: Data and Model Moments

	Data	Model
Std. for log (Equity)	1.059	1.159
Std. for log (Assets)	1.070	1.212
Avg. for Leverage	0.086	0.131
Std. for Leverage	0.051	0.014
Avg. of Revenue/Assets ratio	0.059	0.064
Std. of Revenue/Assets ratio	0.029	0.018
Avg of individual CAR	0.120	0.120
Avg. of Intangible Investment/Revenue ratio	0.261	0.225
Std. of Intangible Investment/Revenue ratio	0.137	0.136
Avg. share of Risky Loans	0.368	0.208
Std. share of Risky Loans	0.223	0.258
Avg. for Markup	0.972	1.151
Std. for Markup	2.383	0.744
Corr.: log (Equity) , Leverage	-0.283	-0.463
Corr.: log (Equity) , Revenue/Assets ratio	-0.311	-0.477
Corr.: log (Intangible Investment) , Leverage	-0.333	-0.241
Corr.: log (Intangible Investment) , Revenue/Assets ratio	-0.273	-0.250
Corr.: log (Intangible Investment) , log (Equity)	0.980	0.870

plot the averages across individual banks for three variables: R&D investment to assets ratio in panel (a), R&D investment to revenue ratio in panel (b), and R&D innovation rates z in panel (c). Higher individual innovation efficiency is directly associated with higher R&D investment in this model. With respect to the absolute levels of R&D investment, group Q5 is about ten times higher than group Q1. We can also see this pattern in panel (c), where innovation rates $z(j)$ are directly impacted by R&D investment. Since the initial distribution of assets positively correlates with R&D efficiency ω, banks with higher ω tend to be larger and have higher revenue. Thus, ratios decrease with ω, as shown in panel (a) and (b).

Quantitatively, for banks with the lowest quintile of ω, 1.96% of initial assets on average are invested for R&D; however, this number is only about 0.52% for those banks with the highest quintile of ω. If we scale R&D investment by bank revenue, the numbers are 28.2% and 10.6%, respectively. The average innovation rate is about 28% for group Q1, while it is as high as 73% for group Q5. Overall, it appears that both the size and effects of R&D investment are economically important.

Next, when we study the impacts of innovations on banks' investments, loan decisions, and overall social welfare, it is helpful to look at banks' risk-taking behaviors. In panel (a) of Figure 4, we plot the average bankruptcy probability across banks within each group. Clearly, the average probability decreases with innovation efficiency, and is mostly driven by the fact that banks with smaller initial capital are more likely to have negative equity values in the second period, as there are both fixed and variable loan issuance costs. We note that this happens even if the choice of risky assets is endogenous and optimal. Small banks optimally calculate the probability of bankruptcy when considering taking more or fewer risks. In addition, bank net worth is positively correlated with ω (as consistent with our data). Therefore, we observe that the average bankruptcy probability decreases with innovation efficiency.

In panel (b) of Figure 4, we compute the average social deadweight loss conditional on bankruptcy. In the event of bankruptcy, however, the size of social deadweight loss (proportional to the value of negative equities) is increasing with innovation efficiency. This is because large banks, with higher ω, also have larger variable costs to repay (from the part of $c_L l^R(j)$) as these banks issue a larger amount of risky loans. The fixed cost is identical across banks, so it will not affect banks' losses differentially. Quantitatively, for banks in group Q1, the average bankruptcy probability is as high as 8.4%, but the probability for group Q5 is only about 0.83%. In contrast, the size of deadweight loss conditional on bankruptcy presents a different pattern, with a value of 0.37 in group Q1 and 4.25 in group Q5.[21] These characteristics from cross-sectional distribution suggest that banks' innovation may have important impacts on risk-taking activities and, consequently, social welfare. We further explore these in the next section.

5.2 The Impact of Aggregate Banking Technology Development

Next, we consider aggregate innovation technology progress so that all banks' innovation efficiency (ω) increases. This can be interpreted as favorable aggregate technology development for banks' R&D (e.g., new technologies for monitoring and managing loans, high-performance computation technologies and more efficient storage methods).

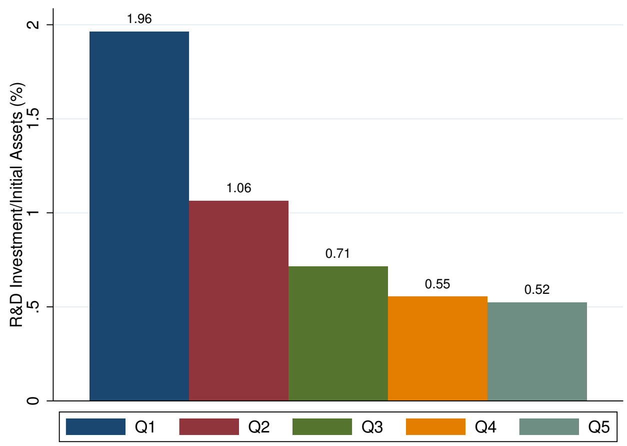
We consider a scenario in which aggregate innovation efficiency increases from the benchmark to about 20% higher. Figure 5 shows that the average bankruptcy probability across the economy increases with aggregate efficiency, and that the aggregate share for risky loans also increases (computed as aggregate risky loans relative to aggregate initial assets). Quantitatively, the average bankruptcy probability increases by approximately 2%, and the aggregate share for risky loans increases by approximately 1%. The increasing pattern is also confirmed when we look at individual banks by groups. Figures D.4 and D.5 in the Appendix provide more detailed illustrations.

Why would higher innovation efficiency increase risky loans? The underlying mechanism works as follows. Banks tend to invest more in R&D as a higher innovation efficiency raises the marginal return of R&D investment. A bank's flow-of-funds constraint (7) implies that a larger R&D investment $i(j)$ reduces the bank's loan allocation given the equity $e(j)$ and the deposit $b(j)$

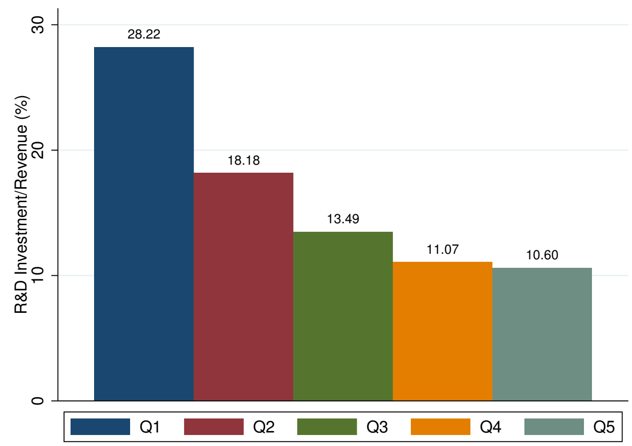
[21]The economy's total initial asset is normalized to 1.

Figure 3: The Cross-Sectional Distribution for R&D Investment and Innovation (by ω Groups)

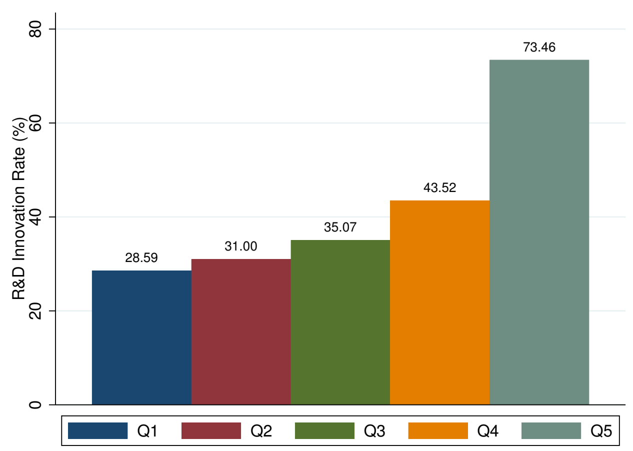
(a) R&D investment/Assets



(b) R&D investment/Revenue



(c) R&D innovation rates

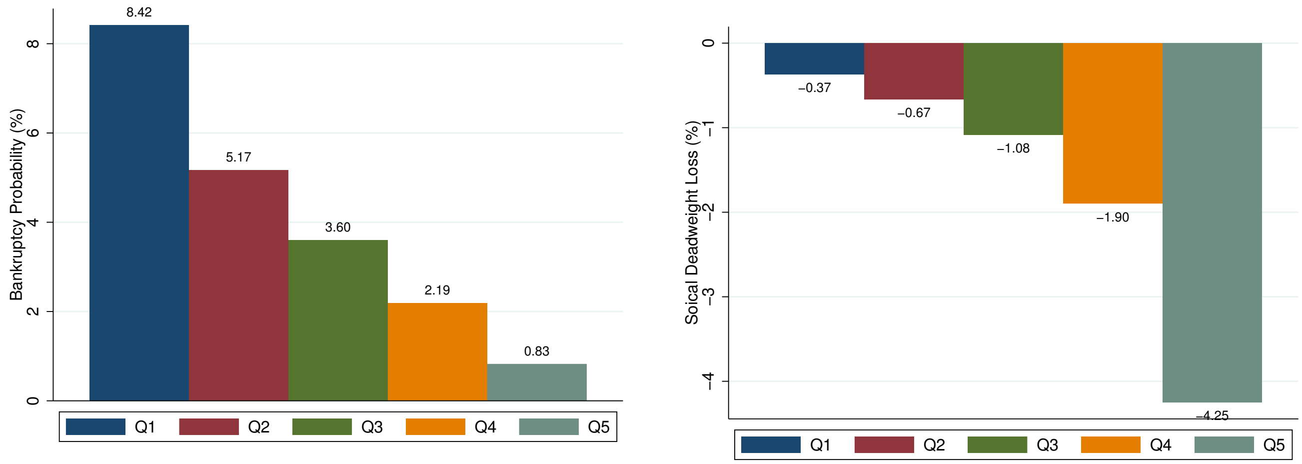


Notes: This figure plots R&D investment and innovation activities for different quintiles. The banks are grouped into Q1 to Q5, according to their R&D efficiency ω from small to large. The y-axis is the average value of each variable within each group. The R&D investment/Asset, the R&D investment/Revenue, and the R&D innovation rate correspond to variables $i(j)/(e(j)+b(j))$, $i(j)/\pi(j)$, and $z(j)$ in the model, respectively. We simulate the model with calibrated parameters and generate a sample of 100,000 observations.

Figure 4: Bankruptcy Probability and Social Deadweight Loss (by ω Groups)

(a) Bankruptcy probability

(b) Social deadweight loss: averages conditional on bankruptcy



unchanged. A lower loan allocation further alleviates the CAR constraint as the denominator in CAR declines. The bank then readjusts the loan portfolio by allocating more risky loans to optimize its profit until the CAR constraint is binding.[22]

Equilibrium effects In the risky loan market, there is imperfect competition among banks. If some individual banks intend to lend more risky loans, they must compete in the loan market and offer lower loan prices, lowering the loan return. Therefore, banks allocate less risky loans in general equilibrium than in partial equilibrium. This pattern is evident from Figure 5. The general equilibrium effects are quantitatively important. Approximately half of the impacts of innovation efficiency on the variables of interest are due to general equilibrium in the loan market.

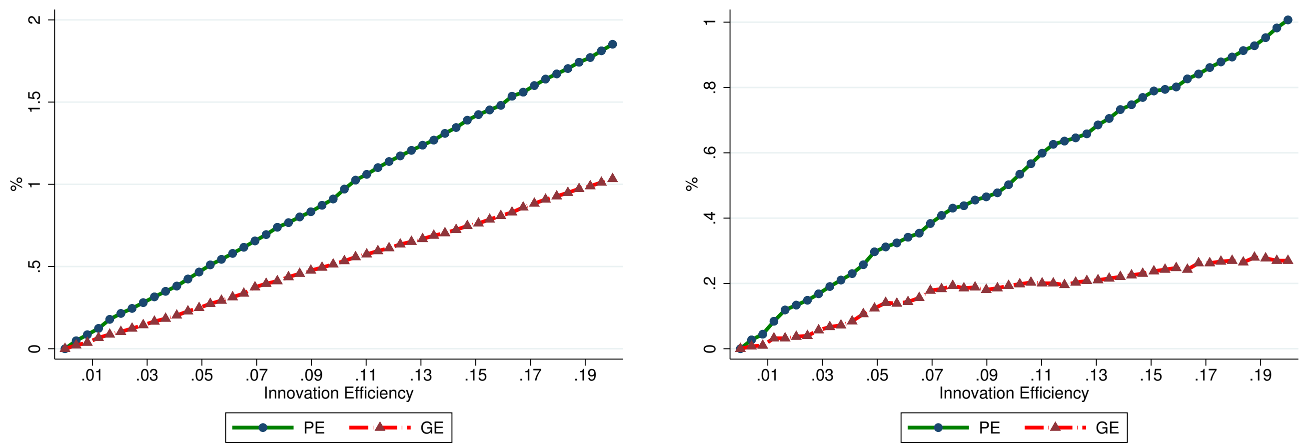
We now document the overall welfare implications of bank innovations. In panel (a) of Figure 6, we compute the changes for total social welfare scaled by total initial assets. We also plot the changes for two important welfare components. Panel (b) reports the total loan issuance costs (roughly accounts for 1.1% of total welfare); and panel (c) reports total social deadweight loss (roughly accounts for 0.35% of total welfare). The figure shows that as aggregate efficiency increases, overall social welfare increases roughly by 0.15% when efficiency increases by 20%. The improved welfare is mainly driven by lower loan issuance costs because banks can better utilize R&D investment to facilitate loan issuance.

However, the total social deadweight loss actually increases despite this overall welfare improvement. This is because individual banks tend to invest more in risky loans when facing a

[22]When the bank increases the risky loan supply, the bankruptcy probability also increases, which tends to lower risky investment. It is typically the first force that dominates; therefore, innovation encourages more risk-taking.

Figure 5: Impacts of Aggregate Technology Change on Banks

(a) Average bankruptcy probability   (b) Aggregate share for risky loans



better innovation technology. As banks have deposit insurance, this cost essentially reflects the moral hazard and increases with aggregate innovation efficiency. At the same time, we note that since loan issuance costs (both fixed costs and variable costs) are reduced, this will lower a bank's loss conditional on bankruptcy. Overall, the loan issuance costs channel still dominates, resulting in improved social welfare.

In summary, our quantitative results suggest that increased aggregate innovation efficiency improves total social welfare because of lower financial intermediation costs. Our results also indicate that banks increase their moral hazard activity, leading to social deadweight loss. Our model proposes a novel channel for understanding how innovation impacts the banking sector.

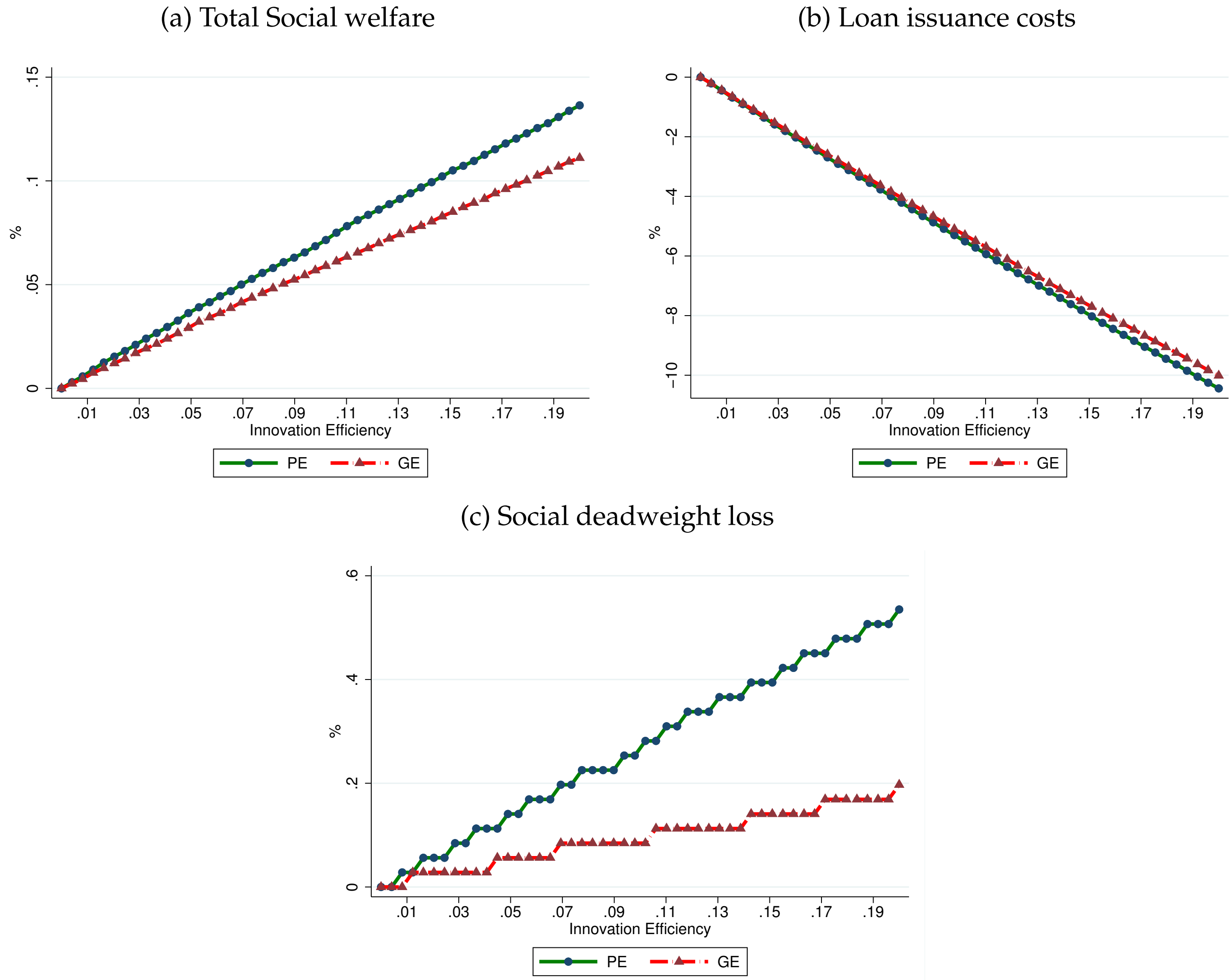
5.3 Policy Implications

R&D Investment Subsidization Policy Closely related to the previous exercise, it is natural to ask what would be the impacts of government policies regarding R&D investment (e.g., tax credit subsidy policy). In this section, we quantitatively evaluate the impacts of this type of policy. In particular, we assume that the government can subsidize a fraction, $\iota \in (0, 1)$, of R&D investment for each bank. The bank's budget constraint becomes $l^S(j) + l^R(j) + (1 - \iota)i(j) = e(j) + b(j)$. All other constraints for the bank remain the same as those in the baseline model. The government uses a lump-sum tax from the representative household to finance this subsidization policy.[23]

In the quantitative exercise, we consider $\iota = 0.20$. Table 8 reports the results on aggregate variables associated with individual banks' characteristics. The overall effect of the subsidization

[23] Thus, when computing total social welfare, we need to subtract the amount of tax credit, $\beta \int_{j=0}^{1} \iota i(j)dj$, from the total welfare.

Figure 6: Impacts of Aggregate Technology Change on Social Welfare



(a) Total Social welfare

(b) Loan issuance costs

(c) Social deadweight loss

Table 8: Impacts of R&D Tax Credit

	Benchmark	With policy	% Change
Total Social welfare	1.105	1.105	0.03
Social deadweight loss (%, relative to total assets)	0.355	0.356	0.25
Loan issuance costs (%, relative to total assets)	1.10	0.96	-12.28
R&D investment/Revenue (%): Q1	28.22	41.69	47.75
R&D investment/Revenue (%): Q5	10.60	14.13	33.29
R&D investment/Assets (%): Q1	1.97	2.79	42.01
R&D investment/Assets (%): Q5	0.52	0.69	32.46
R&D innovation rates (%): Q1	28.60	32.75	14.50
R&D innovation rates (%): Q5	73.46	80.67	9.82
Share for risky loans (%): Q1	37.92	38.31	1.03
Share for risky loans (%): Q5	4.51	4.59	1.79
Average Bankruptcy probability (%): Q1	8.42	8.45	0.35
Average Bankruptcy probability (%): Q5	0.827	0.831	0.50
Social deadweight loss: Averages conditional on Bankruptcy, Q1	0.368	0.365	-0.60
Social deadweight loss: Averages conditional on Bankruptcy, Q5	4.249	4.239	-0.25

policy looks similar to an increase in aggregate innovation efficiency in our baseline model. From an individual bank's perspective, the rate of return from R&D investment relative to its cost now is effectively higher due to tax subsidy. The bank optimally increases R&D investment and reduces this overall loan allocations. The latter further alleviates the CAR constraint. Consequently, the bank optimally adjusts its loan portfolio by allocating more risky projects.

Table 8 shows that the total loan issuance costs of the economy are reduced by about 12%. Banks are encouraged to invest more in R&D, leading to lower loan monitoring/issuance costs. For instance, banks with the highest level of innovation efficiency (group Q5) increase their R&D by almost 32% (scaled by assets). Although the average innovation rate increases by about 9.8%. However, the social deadweight loss also increases by about 0.25%, as banks invest more in risky projects. This pattern can also be seen from the share of risky loans for different groups (Q1 and Q5). The average bankruptcy probability for banks with the lowest level of innovation efficiency (Q1) will increase by about 0.35%. This finding should be interpreted with the fact that, conditional on bankruptcy, the average deadweight loss becomes smaller due to the increased R&D investment and increased innovation rates. Quantitatively, the total effect on social welfare is not that large–only about 0.03%. Thus, when the government considers tax credit subsidy policy for the banking sector, it is crucial to analyze the consequences carefully, for banks' risk-taking incentives must be taken into account cautiously.

CAR regulation policy Previous analysis shows that a bank's innovation activity may have important interaction and dynamics with the bank's risk-taking behavior. Banks' risky investment in loans is typically subject to CAR regulations. We now consider a tightened CAR regulation and investigate the potential consequences. In particular, we assume the CAR in (11),

ξ, increases from 12% to 15%.[24]

Table 9 compares the results with the benchmark economy. Overall, total social welfare increases with a higher capital requirement. There are mainly two counter forces that explain these results. First, banks, on average, have fewer social deadweight losses after the tightening of CAR regulation. This is because banks are required to have less risky loans, holding everything else constant. Second, the economy's total loan issuance costs increase since the bank's innovation declines and safe loan holdings increase. Quantitatively, both channels are important for social welfare change: the former reduces social deadweight loss by about 0.46% (of total initial assets), and the latter increases the cost by about 0.11% (of total initial assets).

We also inspect changes for banks by groups and find that there are heterogeneous responses. Table 9 shows that banks with large ω and large initial capital have smaller risky loan shares, lower bankruptcy probability, and a smaller deadweight loss conditional on bankruptcy. In addition, these banks optimally allocate more initial funds to safe loans to satisfy a tighter capital requirement. A higher safe loan allocation also slightly decreases the R&D investment by about 0.8%. Responses regarding risky loans are similar for banks with lower ω and lower initial capital.

With respect to the policy implications, however, our results should be interpreted cautiously. In our economy, as we highlight the impacts of bank innovation and its interaction with risk-taking behaviors, we deliberately keep the model economy simple and transparent; the simplification is not without prices. The initial distributions of bank capital and deposits are exogenous and fixed. Thus, there are no endogenous dynamics of bank capital, leverage, and risky investments in response to the regulatory changes of CAR constraint. Moreover, banks' entry and exit dynamics may vary when the aggregate environment changes. We leave these interesting and important extensions for future studies.

6 Concluding Remarks

Over the past few decades, banking innovation has drastically changed traditional bank lending business models. However, there is limited research on the detailed channels of these impacts and, consequently, the evaluations for aggregate welfare impacts. In this paper, we study the impacts of banks' innovative investment by constructing a new and comprehensive measurement for innovations. We find that banks' investment can enhance their efficiency and profitability mainly by reducing marginal non-interest net costs.

We construct a bank-year panel data set for Chinese commercial banks, enabling us to uncover several findings. Firstly, banking innovation can improve operating efficiency and prof-

[24]To make results in different exercises comparable, we select those banks that have positive present values with the initial state of $(e(j), b(j))$.

Table 9: Tightening Capital Adequacy Requirement (ζ)

	Benchmark	Increasing CAR	% Change
Total Social welfare	1.10	1.11	1.7
Social deadweight loss (%, relative to total assets)	0.46	0.01	-97.5
Loan issuance costs (%, relative to total assets)	1.07	1.18	9.4
R&D investment/Assets (%): Q1	1.66	1.61	-3.6
R&D investment/Assets (%): Q5	0.578	0.573	-0.8
R&D investment/Revenue (%): Q1	26.3	29.2	10.7
R&D investment/Revenue (%): Q5	13.0	11.3	-12.5
R&D innovation rates (%): Q1	27.5	26.9	-2.3
R&D innovation rates (%): Q5	73.2	72.4	-1.1
Share for risky loans (%): Q1	19.7	3.55	-82.0
Share for risky loans (%): Q5	17.6	1.50	-91.5
Average Bankruptcy probability (%): Q1	10.1	4.28	-57.7
Average Bankruptcy probability (%): Q5	10.1	0.22	-97.9
Social deadweight loss: Averages conditional on Bankruptcy, Q1	-0.18	-0.04	-80.9
Social deadweight loss: Averages conditional on Bankruptcy, Q5	-1.22	-1.11	-8.4

itability, primarily by reducing non-interest-rates costs. We also show that banking innovation may have unintended consequences by increasing bank risk-taking behaviors. These findings are quite robust under a battery of robustness checks.

We then explore the aggregate impacts of banks' innovation through a novel quantitative model. In our model, banks have heterogeneous capital, choose their investment in innovation and risky lending, face regulations on capital requirements, and have limited liability. Improving aggregate new technology can reduce financial intermediation costs and social deadweight loss; however, it will also change a bank's risk consideration and increase the severity of moral hazard when the cost is vastly reduced. We also find several other new implications for R&D investment credit and capital requirement policies (CAR).

Our findings open up several critical questions. For instance, do banks' innovation induce more or less market power? How does endogenous banking innovation transform credit market allocation among shadow banking and traditional banking sectors? How does banking innovation affect banks' systemic risks and monetary policy transmission? We leave these important questions for future research.

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Appendix

A Data Construction

Measurement of Banking Innovation. We measure overall banking innovation by capitalizing various investments in innovation. As a robustness check, we also construct an alternative measure based on banks' technological patent applications.

Innovation has become a critical component of financial business in the banking sector, which helps increase efficiency, promote lending and attract deposits, therefore, results in enhancing banks' market power. For instance, employee training programs improve organizational efficiency. Newly invented software and advanced equipment enable banks to reduce their marginal costs and obtain higher profits. IT adoptions may revolutionize a bank's operational dependency from branch networks to reliance on digital channels and online customers.

It is difficult to define a consistent and economically relevant measure of banking innovation since banks typically do not report research and development spending and, until recently, could not protect their new ideas through patents (Lerner (2006)). Existing literature typically relies on bank IT spending using textual-based measurement (Modi et al. (2022)), or indirect measurement and survey data (Jiang et al. (2022b)). However, China's commercial banks directly report their IT expenses as well as other related expenses as a subchapter termed "FinTech Investment and Innovation Progress" in the annual reports.

In recent decades, China's commercial banks largely invested in IT adoptions. IT expenses reported by state-owned banks all exceed 10 billion CNY by the end of 2021. According to banks' annual reports, IT expenses typically include business system developments, management information systems, software developments, retail services labels, and business models. Business system developments and management information systems are two dominant parts of the expenses. The first one contains settlement systems, online banking systems, foreign exchange and bond trading systems, etc. The second one is a platform for the internal management of the bank, which can provide data support for the bank's decision-making, and help employees perform risk management and facilitate loan origination.

In addition to IT expenses, China's commercial banks explicitly describe their efforts in innovations related to digital banking, employee training and a wide range of technology implications. As pointed out by Modi et al. (2022), some expenditures may be reported without reference to IT expenses due to the classification criteria such as expenses to train employees. Therefore, we choose to construct a measurement of banking innovation by capitalizing banks' innovative-related expenses.

Specifically, following Peters and Taylor (2017) and Belo et al. (2022), we use the perpetual inventory method to capitalize a bank's R&D expense (mostly IT expense) as knowledge capital, and capitalize a small fraction of general administrative expenses as organizational capital. We obtain a measurement of overall banking innovation by accumulating various investments in innovation and summing up with the on-balance sheet intangible assets.[25] To this end, our measurement of overall banking innovation proxies both technological innovation (Chen et al. (2019) and Caragea et al. (2020)) and technology adoptions (Jiang et al. (2022b) and Branzoli et al. (2023)).

[25] Bank's on-balance sheet intangible assets include cross-regional special franchise, rents from AI customer service system patents, deposit box business income, purchased software, etc.

Specifically, for each bank i at time t, type $j \in \{o, k\}$'s capital K_t^j is computed as follows.

$$K_{i,t+1}^j = \begin{cases} (1-\delta^j)K_{i,t}^j + \text{Investment}_{j,t} & \text{if} \quad t > 0 \\ \text{Investment}_{i,t}^j & \text{if} \quad t = 0 \end{cases}$$

in which $j \in \{o, k\}$ denotes organizational and knowledge capital, respectively. To make things simple, we use depreciation rates $\delta^o = 0.2, \delta^k = 0.15$ from Ewens et al. (2019). The investment of organizational capital is to capitalize 30% of general administrative expenses. In the robustness analysis, to highlight more information from IT investment, we choose to capitalize 5% of general administrative expenses, alternatively.

Patent-based Measurement of Banking Innovation. As a robustness check, we also construct banking innovation based on patent applications classification. Patent application is a widely used measure of technological innovation, although patents only measure the output of banks' in-house innovation and do not measure banks' use of new technologies more broadly.

Recent literature aims to measure technological innovation by employing taxonomies to automatically classify patents across different categories of innovations. Chen et al. (2019) apply machine learning to identify and classify patents into seven categories of innovations: cybersecurity, mobile transactions, data analytics, blockchain, peer-to-peer (P2P), robo-advising, and Internet of Things (IoT). Caragea et al. (2020) use deep learning BERT model to classify patents into five FinTech categories: software and techniques for data analytics; fraud detection and cyber security infrastructure; insurance software analytics; investments, lending and portfolio management tools; and mobile transfers and digital wallets. Based on these, Cojoianu et al. (2023) proxy FinTech innovation using the total number of FinTech patents, and find that there's higher competitive pressure from non-financial start-ups by analyzing the effect of FinTech startups on incumbents' innovation behaviors. Jiang et al. (2022c) follow a similar strategy and compute the occupation exposure to Fintech innovations. Such a measure is constructed based on the similarity in the textual information in job task descriptions and that in recent Fintech patent filings. Hasan et al. (2023) apply this methodology to classify China's commercial banks' patent applications. They find banks with more patent-based banking innovation amplify the bank lending channel through the transmission of monetary policy. We follow this strand of the literature and classify banks' patent applications to construct an alternative measurement of banking innovation.

The patent applications are collected from Shanghai Intellectual Property Information Service Platform. We categorize patents based on the International Patent Classification (IPC) codes, which are assigned by the Intellectual Properties Offices to distinguish patent categories. We restrict the sample within IPC class G or H, which excludes the patents that are not related to our definition of banking innovation such as design patents, and patents not related to banks' business operations. Moreover, we also complement the sample by adding patents whose title or abstract contains FinTech-related keywords provided by Chen et al. (2019). The remaining patent applications mostly belong to: G06Q, this IPC code covers data processing systems or technological methods which are usually adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes. The most frequent subcategories of G06Q in our sample are G06Q20, G06Q30, and G06Q40. These three codes cover digital inventions that have applications in payment, e-commerce, and finance, which are defined as a broad range of innovative applications used in the banking sector.

Bank Marginal Cost. We estimate the marginal cost of producing a loan following Berger et al. (2008), which is derived from an estimate of marginal net expenses that is defined to be marginal non-interest expenses net of marginal non-interest income. Marginal non-interest expenses are derived from the following trans-log cost function:

$$
\begin{aligned}
\log\left(NIE_t^i\right) = & g_1 \log\left(W_t^i\right) + \varsigma_1 \log\left(\ell_t^i\right) + g_2 \log\left(q_t^i\right) + g_3 \log\left(W_t^i\right)^2 \\
& + \varsigma_2 \left[\log\left(\ell_t^i\right)\right]^2 + g_4 \log\left(q_t^i\right)^2 + \varsigma_3 \log\left(\ell_t^i\right) \log\left(q_t^i\right) + \varsigma_4 \log\left(\ell_t^i\right) \log\left(W_t^i\right) \\
& + g_5 \log\left(q_t^i\right) \log\left(W_t^i\right) + \sum_{j=1,2} g_6^j t^j + g_{8,t} + g_9^i + \epsilon_t^i,
\end{aligned}
$$

where $NIE_{\theta,t}^i$ is non-interest expenses (calculated as total expenses minus the interest expense on deposits, the interest expense on federal funds purchased, and expenses on premises and fixed assets), g_9^i is a bank fixed effect, W_t^i corresponds to input prices (labor expenses over assets), ℓ_t^i corresponds to real loans (one of the two banks i 's outputs), q_t^i represents safe securities (the second bank output), the t regressor refers to a time trend, and $g_{8,t}$ refers to time fixed effects. We estimate this equation by panel fixed effects with robust standard errors clustered by the bank. Non-interest marginal expenses are then computed as:

$$
\text{Mg Non-Int Exp.} \equiv \frac{\partial NIE_t^i}{\partial \ell_t^i} = \frac{NIE_t^i}{\ell_t^i}\left[\varsigma_1 + 2\varsigma_2 \log\left(\ell_t^i\right) + \varsigma_3 \log\left(q_{it}\right) + h_4 \log\left(W_t^i\right)\right]
$$

Marginal non-interest income (Mg Non-Int Inc.) is estimated using an equation similar to the above (without input prices) where the left-hand side corresponds to the log of the total non-interest income. Marginal net expenses (Mg Net Exp.) are computed as the difference between marginal non-interest expenses and marginal non-interest income. This definition allows for a precise determination of the marginal incremental expenses incurred by the bank, excluding any non-interest-related income generated.

The existing literature argues that banking innovation may facilitate lending by charging a higher rate, or attract deposits with a lower funding cost. In order to investigate whether banking innovation could affect bank performance through these channels. We construct loan markup (see Appendix A.1 in Corbae and D'Erasmo (2021) for details) as a proxy for the bank's performance. The advantage of this measure is that it focuses on loan origination which is the predominant business among all China's commercial banks. The loan markup is therefore defined as:

$$
\text{Loan Markup} = \frac{\text{Interest Return on Loans}}{\text{Cost of Funds} + \text{Marginal Non-interest Net Expenses}} - 1,
$$

where the interest return on loans denotes a measure of price, defined as the ratio of loan interest income over total loans, and the cost of funds plus the non-interest net expenses denote the marginal cost, defined as the ratio of interest expenses from deposits and the central bank borrowings over deposits and central bank borrowings plus marginal net non-interest expenses.

Table A.1 below presents the moments of loan markup related to quantiles of bank size (measured by bank total assets). Figure A.1 plots the distribution of loan markups in our sample.

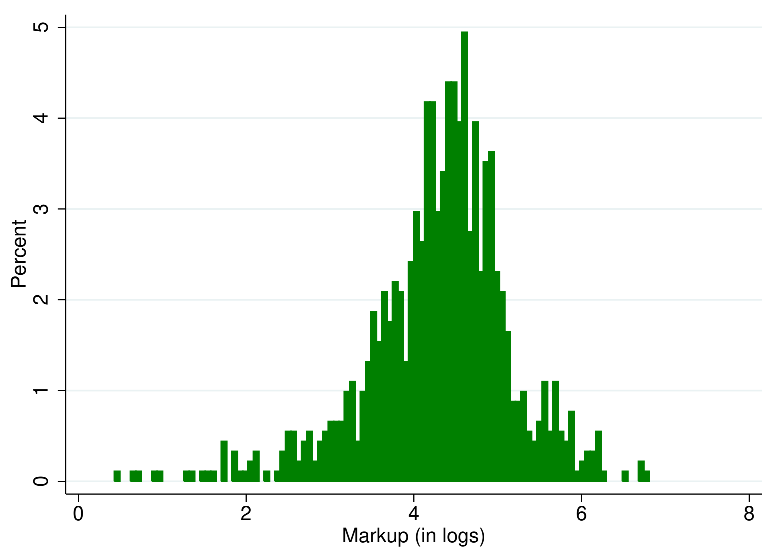
The loan markups are positively correlated with bank size.

Table A.1: Moments Distribution of Loan Markup

	Loan Markup
Average	113.286
Median	81.111
Standard Deviation	242.454
Top 1%	502.42
Top 10%	185.562
Top 25%	120.489
Bottom 25%	50.368
Bottom 10%	28.111
Bottom 1%	3.961

NOTE: This table presents moments from the distribution of loan markups.

Figure A.1: Distribution of Markups



The main variables are defined in Table A.2. The data set covers manually-collected information on banks' IT expenses or R&D expenses. Other bank-level balance sheet data and income statement information are obtained from the China Stock Market & Accounting Research (CSMAR) database. We restrict our sample to banks that survive for more than 3 years and we remove policy banks and foreign-owned banks. We also collect IT expenses, interest expenses on deposits and central bank borrowings, and interest return on loans from their annual reports.

The instrument variable is constructed by the individual bank's initial exposure of graduate employee share, times the national-level growth rate of graduates. Specifically, we include both graduates with either a Master of Science or a Master of Science in Engineering, reported by the

Table A.2: Main Variables' Definition and Construction

Variables	**Definitions**
Banking Innovation	Capitalized Overall Investments in Innovation or Classification on Patent Applications
Marginal Net Expenses	Marginal Non-Interest Expense - Marginal Non-Interest Income
Loan Markup	Interest Return on Loans / (Cost of Funds + Marginal Net Expenses) -1
Interest Return on Loans	Interest Income Loans / Total Loans
Cost of Funds	(Interest Expenses Deposits + Interest Expenses Central Bank) / (Deposits + Central Bank Borrowings)
Non-Performing Loans Ratio	Non-Performing Loans / Total Loans
Risk-Weighted Assets Share	Risk-weighted Loan Assets / Total Lssets
Size	log of Total Assets
Leverage Ratio	Asset to Equity Ratio
Profit-over-Asset	Net Profit / Total Assets
Cost-to-Income Ratio	Operating Expenses / Operating Revenue
Income-over-Asset	Operating Revenues / Total Assets

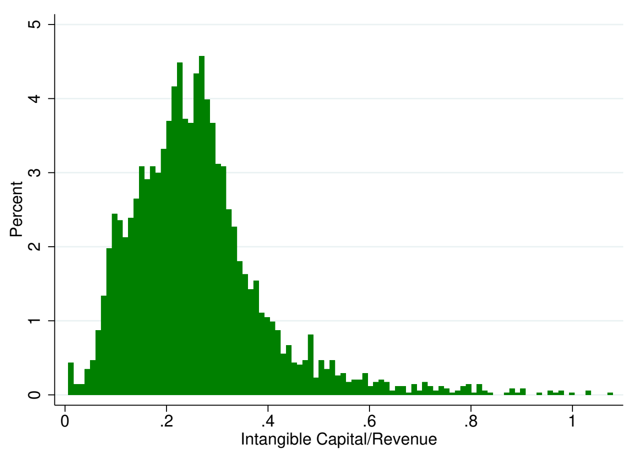
NOTE: This table depicts the definition of main variables. We measure banking innovation by capitalizing overall investments in innovation in the spirit of Peters and Taylor (2017). We also use patent applications to construct an alternative measure of banking innovation. We classify patents based on IPC classification, complemented with a taxonomy method following Chen et al. (2019).

Ministry of Education in China. This is mostly equivalent to the definition of STEM (Science, Technology, Engineering, and Mathematics). We construct IV based on initial exposure instead of a yearly rolling window. This is because there are only a few major banks that have a long-spanned time horizon and update their graduate employee share regularly. Conversely, most of the banks have limited periods and data available only on their initial graduate employee share.

Figure A.2 shows the distribution of banking innovation for all banks (in panel (a)) and for state and nonstate banks (in panel (b)).

Figure A.2: Distribution of Banking Innovation Measurement

(a) All Banks



(b) By Bank types

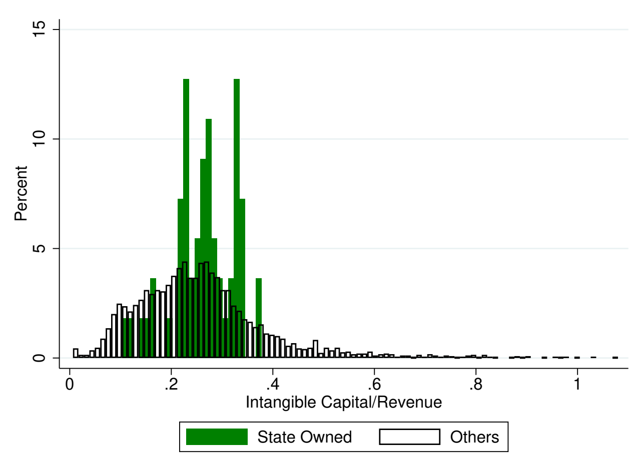


Table A.3: Summary Statistics for Main Variables by Bank Types

	mean	sd	p50	p25	p75
Panel A: State Banks (N = 75)					
Banking Innovation (log)	6.894	0.765	7.117	6.414	7.480
Patent-based Banking Innovation	67.239	44.778	67.000	22.000	117.000
Loan Markup (%)	100.980	54.014	89.583	70.953	110.658
Interest Return on Loans (%)	5.732	0.951	5.893	4.825	6.439
Cost of Funds (%)	1.682	0.328	1.609	1.441	1.840
Marginal Non-Interest Net Expenses (%)	0.960	0.492	0.939	0.784	1.153
Capital Adequacy Ratio (%)	14.042	1.804	13.935	12.680	15.220
Non-performing Loan Ratio (%)	1.852	2.607	1.470	1.190	1.580
Risk-weighted Asset Share (%)	0.142	0.365	0.000	0.000	0.000
Size (log)	11.787	0.620	11.847	11.394	12.307
Leverage Ratio (%)	7.080	1.341	7.233	6.232	8.117
Profit/Asset (%)	1.493	0.314	1.442	1.337	1.630
Liquidity Asset Share (%)	45.804	10.203	45.300	39.620	51.870
Interbank Liability Share (%)	9.078	3.729	7.994	6.476	11.414
Loan Asset Share (%)	53.061	3.733	53.702	50.080	55.890
Cost-to-Income Ratio (%)	30.851	4.457	30.130	28.080	33.280
Income/Asset (%)	2.794	0.338	2.789	2.586	3.014
Profit/Asset (%)	1.493	0.314	1.442	1.337	1.630
Panel B: Nonstate Banks (N = 1,991)					
Banking Innovation (log)	1.645	1.304	1.386	0.596	2.358
Patent-based Banking Innovation	12.479	24.208	3.000	2.000	9.000
Loan Markup (%)	99.100	244.335	72.095	36.841	114.595
Interest Return on Loans (%)	6.864	3.462	6.582	5.400	8.049
Cost of Funds (%)	2.103	2.329	1.945	1.593	2.294
Marginal Non-Interest Net Expenses (%)	1.417	1.020	1.420	0.721	2.005
Capital Adequacy Ratio (%)	16.673	25.360	13.840	12.350	16.050
Non-performing Loan Ratio (%)	1.881	1.756	1.535	0.970	2.260
Risk-weighted Asset Share (%)	0.467	1.502	0.000	0.000	1.045
Size (log)	6.336	1.775	6.252	5.191	7.368
Leverage Ratio (%)	8.849	5.931	7.835	6.400	9.418
Profit/Asset (%)	1.512	0.859	1.355	0.963	1.917
Liquidity Asset Share (%)	67.228	314.770	54.285	44.015	68.120
Interbank Liability Share (%)	6.383	8.631	2.991	0.368	9.645
Loan Asset Share (%)	53.234	94.856	50.990	42.776	58.014
Cost-to-Income Ratio (%)	35.830	12.350	34.000	30.030	38.910
Income/Asset (%)	3.028	1.046	2.826	2.329	3.533
Profit/Asset (%)	1.512	0.859	1.355	0.963	1.917

Figure A.3: Average Loan Markup and its Components

NOTE: This figure plots the average level of loan markup and its components. The top left panel is the average loan markup; the top right panel is the interest return on loans from the previous year; the bottom left panel is the cost of funds measured as interest paid to deposits and central bank over total deposits and central bank borrowings; the bottom right panel is the marginal net expenses derived from trans-log function. We demonstrate the aggregate variables in four ways: simple average, weighted by assets, state-owned banks (top 5) only, and top 10 banks only. The pattern verifies our main results in Figure 1. For the individual bank's markup, we define *1+markup* as the ratio between the interest return on loans and the sum of the cost of funds and non-interest net expenses. The magnitude reflects the percentage point.

B Robustness Analysis

This section contains the tables for robustness analysis as described in Section 2.4. Specifically, for instrument variable regressions, since we construct the instrument variable as the bank-level initial exposure to the national-level growth rate, we include bank-fixed effects with bank-level and aggregate-level controls. For bank risk-taking regressions, since the state-owned banks have easier access to batch transfer of their non-performing assets, we also consider the heterogeneity in bank ownership as an additional bank-level control variable.

Table B.4: Cost-reducing Channel: 1st Stage Regression

First Stage	$\text{Innovation}_{i,t-1}$		
	(1)	(2)	(3)
$IV_{i,t-1}$	0.725***	0.403***	0.046**
	(0.018)	(0.022)	(0.206)
Bank Controls	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes
Aggregate Controls	-	Yes	-
Time FEs	-	-	Yes
F Statistics	85.13	119.19	230.82
p-value Kleibergen-Paap rk LM	0.000	0.000	0.0147
Observations	1580	1580	1580

NOTE: This table reports the first-stage regression result for Table 4. The instrument variable is constructed based on bank-level initial graduate employee share multiplied by national-level STEM growth rate, which denotes the initial exposure of individual banks to aggregate-level growth rate.

Table B.5: Effects of Banking Innovation: Loan Markups Decomposition (IV Approach)

	Log(Markup+1)		Int. Ret. Loans		Cost of Funds		Mg. Non. Net Expenses	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\text{Innovation}_{i,t-1}$	0.227***	0.351*	0.656**	1.583*	0.414***	0.638***	-0.490***	-1.281***
	(0.068)	(0.209)	(0.260)	(0.825)	(0.065)	(0.208)	(0.108)	(0.367)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.772	0.072	0.897	0.126	0.723	0.228	0.710	0.344
Observations	715	715	715	715	715	715	715	715

NOTE: This table reports the estimated results of regressing loan markup and its components on banking innovation. Loan markup takes the logarithm with eliminating negative values, consistent with Corbae and D'Erasmo (2021). For each dependent variable, we compare the results between OLS and 2SLS IV estimation. We include bank-level controls and aggregate-level controls, with bank-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.6: Effects of Banking Innovation on Risk-taking (IV Approach)

	Non-Performing Loan Ratio		Risk-Weighted Assets Share	
	OLS	2SLS	OLS	2SLS
$\text{Innovation}_{i,t-1}$	0.868**	0.491	0.149***	0.249***
	(0.356)	(0.776)	(0.015)	(0.014)
Bank Controls	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.409	-	0.610	-
Observations	1337	1337	1580	1580

NOTE: This table presents the results of regressing bank risk-taking measures on banking innovation. We use ex-post risk-taking measured by the non-performing loan ratios, and ex-ante risk-taking measured by the risk-weighted assets share as a robustness test. For each dependent variable, we compare the estimation results between OLS and 2SLS IV estimation described before. We include bank-level controls and aggregate-level controls, with bank-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.7: Effects of Patent-based Innovation: Loan Markups Decomposition

	Mg. Net Exp.			Loan Markups			Int. Ret. on Loans			Cost of Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\text{Innovation}_{i,t-1}$	-0.670***	-0.348***	-0.251**	0.092	0.143	0.158	-0.984***	0.092	0.100	-0.029	0.004	-0.140**
	(0.101)	(0.107)	(0.099)	(0.098)	(0.109)	(0.109)	(0.216)	(0.211)	(0.221)	(0.059)	(0.063)	(0.061)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Time FEs	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
$\mathbf{R}^2$	0.602	0.634	0.722	0.612	0.613	0.653	0.876	0.903	0.906	0.637	0.659	0.712
Observations	760	760	760	760	760	760	760	760	760	757	757	757

This table presents the results of regressing loan markups and its components on the patent-based measurement of banking innovation. Loan markup takes the logarithm with eliminating negative values, consistent with Corbae and D'Erasmo (2021). Bank-level controls, bank and year-fixed effects, and aggregate-level controls are specified when indicated. We run baseline regression for each variable of interest and add aggregate controls or time FEs, respectively. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.8: Effects of Patent-based Innovation on Bank Risk-taking

	Non-performing Loans Ratio			Risk-weighted Assets Share		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Innovation}_{i,t-1}$	0.003	0.074	0.018	0.108***	0.136***	0.078***
	(0.079)	(0.081)	(0.080)	(0.026)	(0.027)	(0.026)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	Yes	-	Yes	Yes
Time FEs	-	-	Yes	-	-	Yes
$\mathbf{R}^2$	0.479	0.484	0.549	0.585	0.591	0.663
Observations	1562	1562	1562	1589	1589	1589

This table presents the results of regressing bank risk-taking measures on the patent-based measurement of banking innovation. Bank-level controls, bank and year-fixed effects, and aggregate-level controls are specified when indicated. Columns (1)-(3) show the results for ex-post risk-taking measured by the non-performing loan ratios. Columns (4)-(6) show the results for ex-ante risk-taking measured by the risk-weighted assets share as a robustness test. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.9: Effects of Banking Innovation: Loan Markups Decomposition (using Growth)

	Mg. Non-Int Net Exp.	Loan Markups	Int. Ret. on Loans	Cost of Funds
	(1)	(2)	(3)	(4)
$\Delta\text{Innovation}_{i,t-1}$	-0.291**	0.177*	-0.345	0.006
	(0.146)	(0.100)	(0.348)	(0.090)
Bank Controls	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.740	0.750	0.891	0.749
Observations	816	816	816	816

NOTE: This table reports the estimated results of regressing loan markup and its components on the growth of banking innovation to capture the time series information. Loan markup takes the logarithm with eliminating negative values, consistent with Corbae and D'Erasmo (2021). We include bank-level controls, bank and year-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.10: Effects of Banking Innovation on Risk-taking (using Growth)

	$\Delta_{i,t}$ Non-performing Loans Ratio	$\Delta_{i,t}$ Risk-weighted Assets Share
	(1)	(2)
$\Delta\text{Innovation}_{i,t-1}$	0.321**	0.022
	(0.162)	(0.141)
Bank Controls	Yes	Yes
Bank FEs	Yes	Yes
Time FEs	Yes	Yes
$\mathbf{R}^2$	0.137	0.142
Observations	1401	1428

NOTE: This table presents the results of regressing bank risk-taking measures on the growth of banking innovation to capture the time series information. We include bank-level controls, bank and year-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.11: Effects of Banking Innovation: Loan Markups Decomposition (Alt. Construction)

	Mg. Net Exp.	Loan Markups	Int. Ret. on Loans	Cost of Funds
	(1)	(2)	(3)	(4)
$\text{Innovation}_{i,t-1}$	-0.180***	0.096**	0.331**	0.042
	(0.065)	(0.044)	(0.167)	(0.041)
Bank Controls	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.735	0.758	0.890	0.730
Observations	833	833	833	833

NOTE: This table reports the estimated results of regressing loan markup and its components on the reconstructed measurement of banking innovation. We capitalized only 5% of general administrative expenses as organizational capital. The results still support our main conclusion. Loan markup takes the logarithm with eliminating negative values, consistent with Corbae and D'Erasmo (2021). We include bank-level controls, bank and year-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.12: Effects of Banking Innovation on Risk-taking (Alt. Construction)

	Non-performing Loans Ratio	Risk-weighted Assets Share
	(1)	(2)
$\text{Innovation}_{i,t-1}$	1.029**	0.024
	(0.427)	(0.018)
Bank Controls	Yes	Yes
Bank FEs	Yes	Yes
Time FEs	Yes	Yes
$\mathbf{R}^2$	0.455	0.657
Observations	1345	1589

NOTE: This table presents the results of regressing bank risk-taking measures on the reconstructed measurement of banking innovation. We capitalized only 5% of general administrative expenses as organizational capital. The results still support our main conclusion. We include bank-level controls, bank and year-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.13: Effects of Banking Innovation on Bank Efficiency (IV Approach)

	Cost/Income		Income/Asset		Profit/Asset	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\text{Innovation}_{i,t-1}$	-1.606***	-15.588***	0.289***	0.954***	0.184***	1.340***
	(0.566)	(2.463)	(0.040)	(0.163)	(0.062)	(0.258)
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.748	0.638	0.824	0.785	0.528	0.396
Observations	1116	1145	1277	1307	1277	1307

NOTE: This table presents the results of regressing bank alternative efficiency measures on banking innovation. Banking innovation significantly reduces a bank's cost-to-income ratio and increases profit and income. The results support our main conclusion. We include bank-level controls, bank-fixed effects, and aggregate-level controls. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

Table B.14: Cost-reducing Channel: Heterogeneous Effects of Banking Innovation

	(1)	(2)	(3)	(4)
$\text{Innovation}_{i,t-1}$	-0.223***	-0.191***	-0.177***	-0.121
	(0.067)	(0.066)	(0.066)	(0.078)
$\text{Innovation}_{i,t-1} \times \mathbb{I}^{\text{High NPL}}$	0.054***			
	(0.017)			
$\text{Innovation}_{i,t-1} \times \mathbb{I}^{\text{State-owned}}$		-0.303*		
		(0.169)		
$\text{Innovation}_{i,t-1} \times \mathbb{I}^{\text{High Size}}$			-0.021	
			(0.026)	
$\text{Innovation}_{i,t-1} \times \mathbb{I}^{\text{High Profit}}$				-0.073
				(0.049)
Bank Controls	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.747	0.745	0.745	0.745
Observations	1580	1580	1580	1580

NOTE: This table presents the results of regressing marginal cost on the banking innovation with interacted terms as specified. We capture the risky bank groups, high markup group, and large size group by defining dummy variables $\mathbb{I}^{\text{High NPL}}$, $\mathbb{I}^{\text{High Markup}}$, $\mathbb{I}^{\text{High Size}}$, which equals one if bank i's respective variable exceeds the median at year t, and zero otherwise. The dummy variable $\mathbb{I}^{\text{State-owned}}$ indicates whether banks are state-owned. We include bank-level controls, bank and year-fixed effects. The numbers in the parentheses indicate robust standard errors. The asterisks denote the levels of statistical significance: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021.

C Numerical Computation Algorithms

We estimate the key parameters of the model by simulated method of moments (SMM), which minimizes the distance between moments from real data and simulated data. Let us call m the vector of moments computed from the actual data, and the moments generated by the model with parameters vector β. The SMM procedure searches the set of parameters that minimizes the weighted deviations between the actual and simulated moments:

$$(m - \hat{m}(\beta))' W (m - \hat{m}(\beta)),$$

where the weighting matrix W can adjust for the fact that some moments are more precisely estimated than others (say, using the inverse of data variance as weights). In practice, we can start with the identity matrix. For a given parameter vector, we need to find the model's equilibrium. The following steps describe the details of finding the equilibrium.

1. First, we guess some initial loan prices and quantities for the aggregate variables, (p^S, p^R, l^S,l^R). Then, for the given parameters and initial prices, we need to solve individual banks' optimization problems (see the details below)

2. We then simulate a large panel of banks and obtain aggregate loan prices and quantities using the CES demand functions and price functions

3. Check the implied aggregate prices and quantities with the initial guesses. If they are not close enough, we need to further update the guesses in the previous round.

For calibration and moment matching, we need to repeat the above equilibrium-finding procedures. We use Nelder-Mead Algorithms to help find the best parameter vector. For solving optimization problems, some of the important details are listed below.

- For solving the individual optimization problem, first, in general, we can denote the set of first-order conditions as:

$$\begin{aligned}
\text{F.o.c for R\&D:} \quad \lambda(j) &= \beta\left[\chi + (1-\chi)\mathbf{I}(j)\right]\left\{c_L\left[l^S(j) + l^R(j)\right] + c_F\right\}\frac{\partial z(j)}{\partial i(j)}, \\
\text{F.o.c for } l(j)^S\text{:} \quad \lambda(j) + \phi(j)\xi &= \beta\left\{1 + p^S - c_L[1 - z(j)]\right\}\left[\chi + (1-\chi)\mathbf{I}(j)\right]. \\
\text{F.o.c for } l(j)^R\text{:} \quad \lambda(j) + \phi(j)\xi\psi &= \beta\chi\left[1 + \frac{\epsilon - 1}{\epsilon}p^R(j)\right] - \beta\left[\chi + (1-\chi)\mathbf{I}(j)\right]c_L[1 - z(j)].
\end{aligned}$$

  Or, in short notations, we can denote these as:

$$\begin{aligned}
\lambda &\equiv F_i, \\
\lambda + \phi\xi &\equiv F_S, \\
\lambda + \phi\xi\psi &\equiv F_R.
\end{aligned}$$

  If further simplifying these equations and canceling out all the unknown, endogenous multipliers, we can have just one equation as follows, which sometimes could be convenient for the solution.

$$F_i(\psi - 1) = \Psi F_S - F_R.$$

In general, there are mainly two possible cases.

- Case 1: if the CAR constraint is binding, $\phi(j) > 0$. In this case, first using budget constraint, CAR, we can have the following set of conditions that should be satisfied with the optimal solution:

$$\begin{aligned} 0 &= e(j) + b(j) - l(j) - i, \\ l(j) &= l(j)^S + l(j)^R, \\ e(j) - \xi\left(l(j)^S + \Psi l(j)^R\right) &= 0, \\ i &\geq 0, l(j)^S \geq 0, l(j)^R \geq 0. \end{aligned}$$

These conditions require that the initial values for the bank's capital and deposit, $e(j)$ and $b(j)$, should satisfy the following equations:

$$\begin{aligned} l(j) &= e(j) + b(j) - i, \\ (\Psi - 1)\,\xi l(j)^R &= e(j) - \xi l(j), \\ l(j)^S &= l(j) - l(j)^R, \\ \frac{e(j)}{\xi\Psi} &\leq l(j) \leq \frac{e(j)}{\xi}, \\ i &\geq 0, \end{aligned}$$

or, we can express it as constraints for the choice of i:

$$\begin{aligned} e(j) + b(j) - \frac{e(j)}{\xi} &\leq i \leq e(j) + b(j) - \frac{e(j)}{\xi\Psi}, \\ 1 - \frac{e(j)}{\xi(e(j)+b(j))} &\leq \frac{i}{e(j)+b(j)} \leq 1 - \frac{e(j)}{\xi\Psi(e(j)+b(j))}. \end{aligned}$$

Note that for a given i, $(l(j)^S, l(j)^R)$ can be determined subsequently. If there is a solution in this case, we need to check all the conditions above; If there are multiple solutions, then we need to pick up the one that gives the best expected value. Numerically, we need to first find the feasible space for i and make sure it is not empty. Within the feasible interval for i, we can use either grid search method or use Golden search method to find the best i to maximize the bank's expected value (or to minimize the squared errors in Focs). There could be multiple solutions; For each one, we need to check all the required consistency conditions and then compute $(l(j)^S, l(j)^R)$ and the expected value. Lastly, we pick up the best solution for i (if any).

- Case 2: if CAR is not binding; $\phi(j) = 0, e(j) - \xi\left(l(j)^S + \Psi l(j)^R\right) \geq 0$:

$$\begin{aligned} l(j) &= e(j) + b(j) - i \\ l(j) &= l(j)^S + l(j)^R, \\ e(j) &\geq \xi\left(l(j)^S + \Psi l(j)^R\right), \\ i &\geq 0, \end{aligned}$$

and the Focs can be presented as:

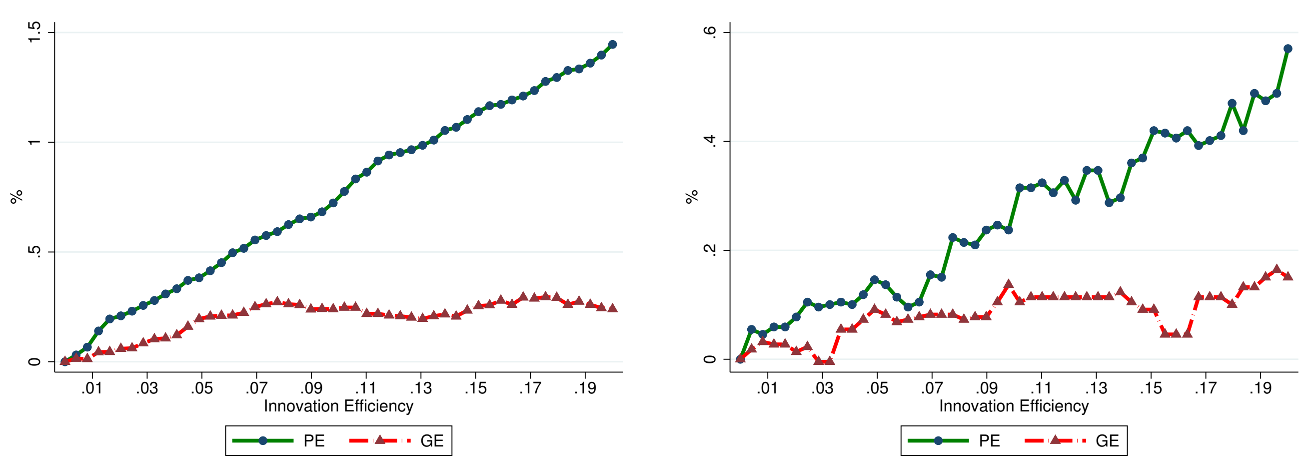
$$\begin{aligned} \mu(j) &\equiv F_i, \\ \mu(j) &\equiv F_S, \\ \mu(j) &\equiv F_R. \end{aligned}$$

For this case, we need to solve for $i, l(j)^S$ simultaneously, ($l(j)^R$ can be determined subsequently then). If there is a solution in this case, we also need to check all the conditions above. Since we have two endogenous choices to find, the problem is nonlinear, with bounds and constraints. A robust and fast method in this case we use is: for each i in the grid space, first find the feasible space for $l(j)^R : 0 \leq l(j)^R \leq \frac{e(j)-\xi l(j)}{(\Psi-1)\xi}$; then using Golden search method to find the best $l(j)^R$ so that the bank's expected value is maximized; if we find such a solution, then compute $(l(j)^S, l(j)^R)$ and related values; if not, move on to the next point of i. Eventually, we need to compare and maximize over the two possible cases (CAR is binding or not).

D Appendix for Quantitative Results

Figure D.4: The Impacts of Aggregate Technology on Banks: Risky Share

(a) Share for risky loans: Q1 (b) Share for risky loans: Q5

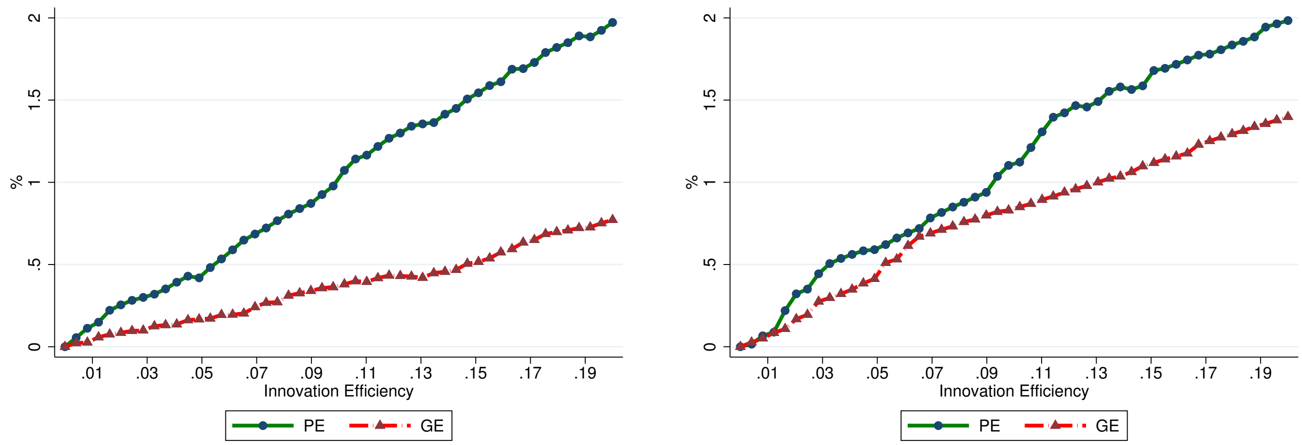


NOTE: These figures show results when we change the aggregate innovation efficiency for the whole banking sector. "Q1" and "Q5" refer to the group of banks with the first and the highest quintile of ω, respectively. "Share for risky loans" is computed as the average of individual risky shares within each corresponding group.

Figure D.5: The Impacts of Aggregate Technology on Banks: Bankruptcy Probability

(a) Average Bankruptcy Probability: Q1

(b) Average Bankruptcy Probability: Q5



NOTE: These figures show results when we change the aggregate innovation efficiency for the whole banking sector. “Q1” and “Q5” refer to the group of banks with the first and the highest quintile of ω, respectively. “Average Bankruptcy probability” is computed as the average of individual Bankruptcy probability within each corresponding group.