Banking Innovations in China: Evidence and Welfare Implications[*]

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October, 2023

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 the effects and, consequently, the evaluations for 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. We document that banking innovations can reduce marginal net costs, improve efficiency, and increase bank risk-taking. The findings are robust under a battery of sensitivity checks. We then construct a novel quantitative heterogeneous banking model in which the banks with heterogeneous capital choose investment in innovation and risky lending, face regulations on the capital requirement, and have limited liability. Quantitative analysis indicates that an improvement in aggregate new technology can reduce financial intermediation costs and social dead-weight loss. However, it will also change the bank's risk consideration and exacerbate moral hazard problems when the cost is largely reduced. We also find several other 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

[*]We are grateful to Yan Bai, Kaiji Chen, Haoyu Gao, Bo Li, Kai Li, Xuewen Liu, Kjetil Storesletten, Pengfei Wang, Yi Wen, and seminar participants at Peking University, the 4th China International Conference in Macroeconomics, 2023 China Financial Research Conference, the 6th Annual International Conference of China and Development Studies for valuable comments and suggestions. The authors acknowledge the financial support from the National Natural Science Foundation of China (72150003, 72022011) and the grant from Shenzhen Municipal Government (No. 1210614103). The usual disclaimer applies.

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1 Introduction

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

We study the impacts of banking innovations both empirically and quantitatively.[1] First, using bank-level dataset from China - the second largest and emerging country, we find that banking innovations can improve efficiency, primarily by reducing non-interest costs but not so much on deposit costs and loan revenues. Thus, the costs of financial intermediation can be reduced when technology advances in the banking sector, as in Diamond (1984) and Philippon (2010). Second, we further analyze the impacts of banking innovations on individual banks' lending and risk-taking decisions and 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 reach several new insights into the literature.

In the empirical analysis, we first construct bank-level panel data for China. In particular, Chinese commercial banks in the last two decades have made efforts to improve 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 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 investment or R&D investment (see Data 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 on loans and deposits by constructing bank markups on loans and estimating bank cost structure for interest-rates-related and non-interest-related costs.[2]

[1] Banking innovations encompass a wide range of advancements and technological improvements. By banking innovation, we mean to include technological innovations, changes in bank business credit models, and risk management improvements, excluding bank new products to depositors and individual customers. Thakor (2020) provides an excellent review of the definitions and implications of banking innovations.

[2] Non-interest rate related costs may contain monitoring and/or loan issuance costs, mainly daily operating costs, labor costs, and other capital costs. The approach we use follows Berger et al. (2008) and also recently Corbae and D'Erasmo (2021).

For the bank-level panel data, we find that an increase in the initial level of banking innovation is associated with a significant reduction in marginal non-interest costs later on, which may further deliver an increase in loan markups. Besides, banking innovations are more likely to bring 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 a new instrument variable. We exploit variations in individual banks' initial exposure to the changes of national college graduates since different banks tend to have different compositions of labor skills in their workforce. In addition, we make use of patent data to classify banking innovations. We find consistent patterns that the patent-based measurement of banking innovation significantly reduces bank marginal net costs.

Motivated by the 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 the R&D investment, banks choose to lend to safe and risky types of borrowers. Banks are subject to the government's Capital Adequacy Ratio (CAR) requirement, which regulates banks' risk-taking behaviors. 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 pretty good fit to the empirical patterns. For instance, the model can produce positive correlations between R&D investment and banks' profitability, as observed in the empirical analysis. We also find that the mean and dispersion of markup rates for banks can be accounted for quite well - which disciplines banks' cost structures and can have important influences on aggregate efficiency.

Based on the quantitative model, we first 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 fixed and variable costs. This has an important consequence: even if holding banks' all activities unchanged, it will lower the bank's loss (or the non-performing loans) conditional on bankruptcy, consistent with the previous empirical findings. Meanwhile, when enjoying better technologies, the bank re-adjusts investment portfolios by reducing the optimal R&D spending and shifting more to risky lending on the margin. The risk-shifting is at the cost of moral hazard because of the deposit insurance, and it increases with a higher aggregate innovation efficiency. Individual banks interact with each other in the general equilibrium. We find that the equilibrium effect is quantitatively important, accounting for approximately half of the changes in the loan market.

Regarding aggregate welfare implications, we find that an increase in aggregate innovation efficiency improves total social welfare due to the reduction in financial intermediation costs. However, banks also increase moral hazard activities, leading to a higher social deadweight loss. Quantitatively, the increased moral hazard problem and social deadweight loss are dominated by reduced costs, resulting in a net increase in social welfare. Therefore, our structure model analyzes the detailed channels through which technological innovation impacts the banking sector.

We further explore the implications for two R&D-related policies. R&D investment tax-credit policy is widely adopted across countries. We evaluate this policy's impacts 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. The results show that the policy reduces total loan issuance costs by about 12%. The total effect on social welfare is modest, only about 0.03%. This is because banks re-adjust their lending portfolios toward risky assets, resulting in a higher social deadweight loss. Thus, the tax-credit subsidy policy should be considered more prudently due to the 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 innovation margin. The 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 will also reduce investment in R&D since the shadow cost of initial capital becomes higher. Consequently, the bankruptcy risk becomes lower, but the average loss conditional on bankruptcy becomes larger. Overall, the first effect dominates, and the total social welfare increases.

The above policy experiments indicate that the banking innovation channel is a vital margin to consider, which is merely studied in the literature. Our paper contributes to further understanding the policy and welfare implications when banks are affected by technological progress and banking innovation.

Related literature First, our paper contributes to the existing studies by further understanding the impacts of innovation within the banking industry.[3] By decomposing banks' cost structure, we investigate the detailed channels through which the innovations affect banks' efficiency, in line with Diamond (1984) and Philippon (2015).

Many papers in the banking innovation literature explore 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] Early

[3] There is a broad literature on the impacts of innovation and new technology (e.g., among others, 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.

research such as Berger (2003) provides descriptive evidence on banks' adoptions of new IT and financial technologies and document 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 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 unintendedly increase bank risk-taking or fragility (Beck et al., 2016, Zhao et al., 2023). The 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).

Second, our paper provides a comprehensive measurement of banking innovation. We cover various investments in innovation, including IT investment, and patent-based measurement as a robustness check. Banking innovations contain digital banking, IT, human capital development, and a wide range of technology implications. However, it is difficult to gauge the banking applications of various technologies. 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 an overall measurement of banking innovation based on the perpetual inventory method in the spirit of Peters and Taylor (2017) (see Appendix A for details of the method). More recently, Chen et al. (2019), Fu and Mishra (2022) and Jiang et al. (2022c) classify banking innovations by employing taxonomies to classify information from patents across different categories of innovation activities. Therefore, following these literature, we consider a patent-based measurement of banking innovation as a robustness check.

This paper also relates to the new strand of literature that focuses on the roles of China's banking system and its interaction with regulations and monetary policies. Cong et al. (2019) use loan-level data and find that the credit expansion during China's large-scale fiscal stimulus episode in 2009-2010 dis-proportionally 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. 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 data set. Li et al. (2022) exploit loan-level data and study the impacts of implementing Basel III capital regulation on banks' risk-taking, both empirically and quantitatively. Hasan et al. (2023) find

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

that lending-related banking innovation amplifies monetary policy transmission through bank lending channels.[6] Differently, we focus on investigating banking innovation and its aggregate and distributional impacts, both empirically and quantitatively.

Our quantitative model with heterogeneous banks is related to 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) focus more on the relationship between bank competition and profitability with theoretical studies. Corbae and D'Erasmo (2021) study banking industry dynamics in business cycles quantitatively. Li et al. (2022) study the impacts of Chinese banking regulation changes over business cycles. This paper introduces a novel cost structure and R&D investment that can alter the costs. The analytical framework builds on influential theory works such as Diamond (1984) and Philippon (2010), and is closely related to the macro and growth literature (such as Acemoglu et al., 2018, Akcigit and Kerr, 2018, Klette and Kortum, 2004). Our paper differs from the existing quantitative banking studies by focusing on the impacts of banking innovations on individual bank performances and aggregate social welfare.

The rest of this paper is organized as follows. Section 2 presents empirical facts on the role of banking innovation on bank cost structure, efficiency, and risk-taking. Section 3 introduces a theoretical model with heterogeneous banks in which investments in innovation and loan portfolio decisions are made by banks subject to capital requirement constraints. Section 4 solves the quantitative model and calibrates it to China's bank panel data. Section 5 implements numerical simulation on welfare implications of banking innovations. Section 6 concludes the paper.

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 using a rich set of controls and instrumental variables. In addition, we find banks with higher stock of intangible capital, else equal, tend to have higher risk-taking. Finally, we confirm our results with several robustness checks, including using alternative patent-based measurements of banking innovation, alternative bank efficiency measures, different econometric methods, etc.

[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, focusing on SME and consumer loans, does not directly compete with traditional banks. Thus, we focus on banking innovation within the traditional banking sector.

2.1 Data and Variables

We construct a bank-level panel data mainly using two sources. We obtain banks' balance sheet information from China Stock Market & Accounting Research (CSMAR) database, including loans, deposits, and other detailed balance-sheet characteristics. We mutually collect other variables from banks' annual reports, including interest-related income and cost structures, IT expenses, etc. We have information on 310 banks from 2008 to 2021, accounting 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, platform developments, digital banking services, etc. 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, a small fraction of the general administrative expenses as organizational capital, and sum up them with on-the-balance-sheet intangible assets, which include banks' patents and special franchises, etc. Such measurement can be regarded as capitalized investments in innovation (see Babus et al., 2023, Corrado et al., 2020, Kogan and Papanikolaou, 2019, Peters and Taylor, 2017 and among others). It has been suggested that knowledge and organizational capital may influence firms' operating efficiency and productivity, e.g., Bartel et al. (2007), Crespi et al. (2007). In the spirit of De Ridder (2021) and Corrado et al. (2022), we believe such measurement can best reflect overall banking innovation in China. Following the FinTech innovation literature, we also construct patent-based measurement of banking innovation as a robustness check in Section 2.4.

To examine the predominant channel through which bank investments in innovation affect bank performance and subsequent behaviors, we focus on the performance of banks in the context of deposits and loans, which constitute the primary financial activities in China's banking sector. We aim to shed light on banking innovation's key drivers and implications.

There are two types of bank costs in general: cost of funds (interest-related) and non-interest cost. We compute the interest-related cost as the interest paid to deposits and central bank borrowing. We express the non-interest cost by estimating the marginal cost of producing a loan, 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. 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) to compute loan markups as the ratio between the interest return on loans and the sum of the cost of funds and non-interest cost. The construction details of variables are described in Appendix A.

Figure 1 plots the asset-weighted aggregate level of loan markups along with its components. The time series span from 2008 to 2021. The asset-weighted average is calculated using the individual bank's asset over the total asset in each period as the weight. Consistent with Corbae and D'Erasmo (2021), the average loan markups have risen since banks made great efforts to increase their profitability and strengthen competitive advantages during the sample periods. The average interest return on loans and the average cost of funds are relatively stable, while the average marginal 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 the loan markup.

The average cost of funds remains relatively stable even if China has recently experienced a falling interest rate. This is because the People's Bank of China (PBOC) has established the bank deposit ceiling regime for a long time which prohibited commercial banks from changing deposit rates flexibly. The average interest return on loans fluctuates but declines from 7% to 5% in the sample period due to expansionary monetary policies aiming to decrease firms' financing costs and declining interest rates along with economic slowdown. Notably, the marginal net expense trend has consistently declined over the sample period. This could result from banks' incentives to improve efficiency and enhance profitability via investments in innovation.[7]

[7]Notice that the declining trend for marginal net expenses during 2017 is not driven by the New Capital Regulation on off-balance sheet non-standard products in China since we construct the marginal net expenses by trans-log function, which controls the financial asset trading related to off-balance sheet products.

Figure 1: Aggregate Level of Loan Markup and its Components

NOTE: The four panels are organized as follows. 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, computed following empirical banking literature. We use assets as weights for the aggregate averages. In Appendix Figure A.3, this pattern still exists where we demonstrate the aggregate variables in four different ways: simple average, weighted by assets, state-owned banks (top 5) only, and top 10 banks only. 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.

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

Banks' investments in innovation could also interact with banks' investment in risky loan assets and, therefore, bank risk-taking behaviors. Current studies have proposed various bank risk-taking measurement methods from different perspectives.[8] With bank-level data, the most frequently used proxies are the non-performing loans ratio and risk-weighted assets share. The non-performing loans ratio can reflect the quality of bank loan assets and the ex-post credit risk bore by the bank. The risk-weighted asset ratio measures the bank's ex-ante risk-taking, including loan risk and market risks associated with other assets. We use the latter one as an alternative measurement of bank risk-taking for robustness checks. Appendix Table A.3 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	91.030	334.528	5.000	2.000	34.000
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.

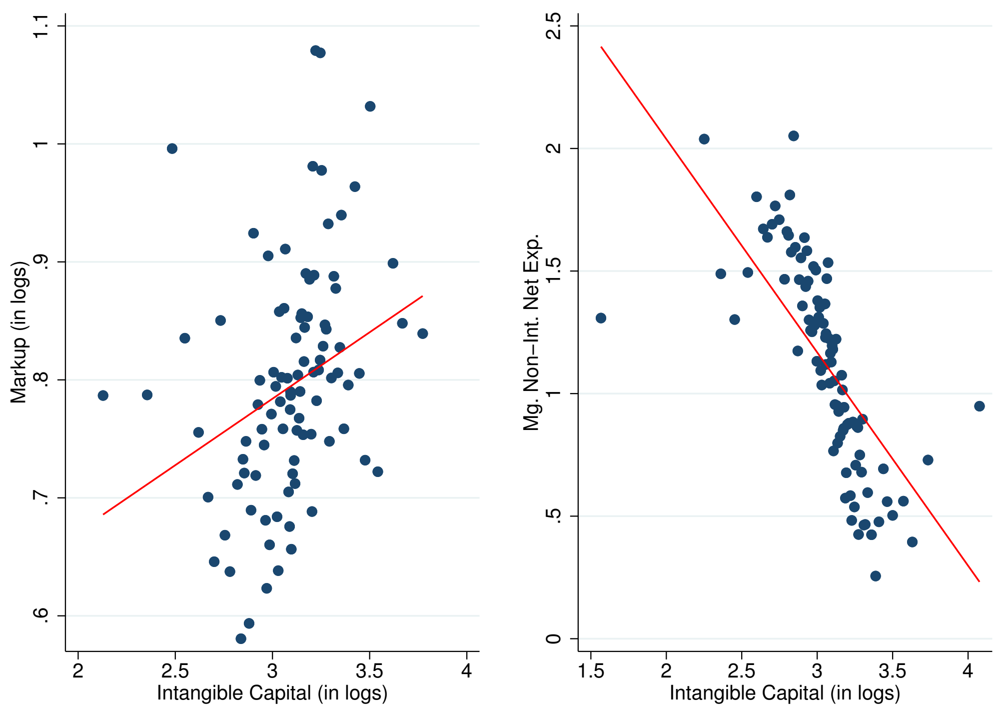
For a first look, Figure 2 indicates a clear positive relationship between banking innovation

[8] Ideally, we should keep track of each loan's pricing and default history to measure the bank's loan risk and compute the bank's risky loan share. With detailed loan-level data, researchers can compute risky loans based on borrowers' credit ratings or other borrower-level exogenous risk exposure features. For instance, Li et al. (2022) proxy safe loans by either categorizing firms' credit ratings which are above AA- or linking loans to borrowers if they are state-owned enterprises (SOEs) since SOEs are commonly regarded as less risky compared to private-owned enterprises (POEs) in China.

[9] State banks exhibit higher loan markups, lower interest return on loans, and lower risk-taking behaviors but smaller marginal net expenses and cost of funds. In contrast, non-state banks demonstrate comparatively lower levels of innovation and smaller markup on loans, with higher interest return on loans, higher risk-taking, and higher marginal net expenses and cost of funds. Further analysis of the heterogeneous impacts of banking innovation across different ownership 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.

and loan markups shown in the left panel, and the right panel displays a negative relationship between banking innovation and marginal non-interest net expenses. The figure depicts the scatter plots by controlling bank fixed effects. We proceed with further econometric analysis below.

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



NOTE: The left panel shows the scatter plots between the measurement of banking innovation and loan markups; the right panel shows the scatter plots between banking innovation and marginal non-interest net expenses.

2.2 Econometric Specification

We run panel regressions to document how innovative technology affects bank profitability structure (i.e., cost 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; 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 one-year benchmark deposit rate set by People's Bank of China at year $t-1$. We control for bank fixed effects (δ_i) and, alternatively, time fixed effects (δ_t) as a robustness check.

One concern with the panel regression analysis is the potential endogeneity arising from the bank heterogeneity along various dimensions and unobservable or omitted factors simultaneously affecting innovation and outcome variables. To mitigate the 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 possessing 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) and Philippon (2016)). This instrument for bank-level graduate employee share should be read as the interaction of the national STEM graduate growth with bank-level initial exposure. This 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 its decomposition

Banking innovation may not only reduce costs to improve loan profitability but also help banks to 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 return on loans, interest-related cost of funds, and marginal non-interest net expenses. We subsequently conduct regression on banking innovation for each variable by adding aggregate controls or time FEs. Since fewer banks report sufficient cost structure information, interest incomes, and interest expenses, the sample size is restricted to be smaller for the following analysis.

We implement the unbalanced bank panel regression based on specification (1). Table 2 reports the baseline estimation results for the markup on bank loans and its decomposition. Specifically, Column (1) indicates that banking innovation significantly and negatively impacts 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 FEs. The results remain valid in Columns (2) and (3) when aggregate controls or time FEs are considered. Column (4) shows that banking innovation significantly and positively affects loan markups. A 1% increase in the initial bank's innovation level is associated with a 0.132% increase in markups on bank loans. We see that the increasing loan markup is contributed by reducing marginal net expenses, while the impact of banking innovation on the rest two interest-related terms is ambiguous. 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.

Banking innovation is significantly associated with a reduction in marginal non-interest expenses. However, it does not unambiguously contribute to a higher loan return or a smaller interest-related cost of funds. Since the overall banking innovation does not increase interest return on loans nor decrease the cost of funds, the marginal cost-reducing channel dominates the resulting increase of markups on bank loans. The 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 the overall innovative practices and technological applications contribute to reducing loan origination and monitoring costs. For instance, banks may invest in mobile app development to enable their business to be less branch-reliant, reducing bank operating costs.[10] Banks may also invest in advanced machines to replace redundant labor, reducing labor costs. Moreover, Chinese commercial banks invest in building 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 the findings in corporate finance literature that focus on intangible capital. By capitalizing firms' R&D expenses and 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 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

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

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

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 FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Time FEs	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Observations	715	715	715	715	715	715	715	715	715	715	715	715
$\mathbf{R}^2$	0.710	0.710	0.755	0.770	0.772	0.794	0.888	0.897	0.900	0.652	0.723	0.743

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). 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.

results are consistent with the baseline evidence, as the 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 a higher amount of 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 also improve a bank's ability to process information and monitor the borrower more effectively and efficiently, therefore mitigating risk-taking. However, it still remains insufficiently studied in existing research for the question of how banking innovation could affect bank risk-taking.

In this section, we empirically document the impacts of banking innovation on risk-taking using a similar estimation strategy as before. We consider two measurements of bank risk-taking,

[12] For example, the risk-shifting channel could work as follows. First, banks that adopt new technologies such as artificial intelligence, blockchain, cloud computing, and data analytics, may be able to improve their operating efficiency and such positive cost-reducing effect shifts banks to 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 potential marginal borrowers. Second, technological innovation or IT adoption allows banks to expand their power to new lending markets, and offer innovative 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 bank technological capabilities and often serve riskier borrowers or facilitate loans with less stringent credit criteria if without regulations.

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$_{i,t-1}$	0.865**	0.868**	1.406***	0.295***	0.297***	0.023
	(0.355)	(0.356)	(0.519)	(0.035)	(0.035)	(0.050)
Observations	1337	1337	1337	1580	1580	1580
R^2	0.409	0.409	0.451	0.602	0.603	0.649
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	-	Yes	Yes	-
State Banks	-	Yes	Yes	-	Yes	Yes
Time FE	-	-	Yes	-	-	Yes

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, the non-performing loan ratios, and columns (4)-(6) show the results for ex-ante risk-taking, the risk-weighted assets share as a robustness testing. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

including the non-performing-loan ratio and the share of risk-weighted assets.

Table 3 reports the main results. Columns (1) to (3) and Columns (4) to (6) correspond to the results for the case of NPL ratio and risk-weighted asset, respectively. The results suggest that bank innovation significantly increases bank risk-taking. For instance, Columns (1) and (4) indicate that one percentage increase in the level of banking innovation significantly increases its NPL ratio by 0.865% and increases in bank's risk-weighted asset share by 0.295%, respectively. The positive effects on bank risk-taking remain robust after controlling for heterogeneity in bank ownership and time FEs.

2.4 Robustness Checks

We next conduct a battery of robustness checks. Firstly, we validate the cost reducing channel by only looking at the marginal non-interest net expenses. The results are reported in Table 4.

Column (1) runs 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 the counterpart results in the IV regressions. The IV regressions in Columns (4) to (6) deliver similar results, but the coefficients are higher than our baseline estimates.[13] The first

[13]Two possible reasons can explain larger estimates. First, endogeneity issues may cause the OLS estimates

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***	-0.182***	-0.102*	-0.491***	-0.591***	-2.909**
	(0.026)	(0.040)	(0.060)	(0.033)	(0.087)	(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
Observations	1580	1580	1580	1580	1580	1580
$\mathbf{R}^2$	0.627	0.637	0.752	-	-	-

NOTE: This table reports the estimated results of regressing marginal non-interest net expenses on banking innovation. Bank-level controls, bank and year FEs, and aggregate-level controls are specified when indicated. Columns (1)-(3) show the results of the OLS estimation, and columns (4)-(6) show the results of 2SLS IV estimation. 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.

stage regression and identification test results are reported in Appendix Table B.4. 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 the choice of our instrument variables is reasonable.

We re-estimate Table 2 and Table 3 using 2SLS with the constructed instrument variable, shown in Table B.5 and B.6 in the Appendix. The coefficient signs are consistent with the original estimations at a significant level. The IV estimates are relatively larger than OLS coefficients since our instruments correct for measurement error in the data on bank-level intangible capital that does not arise at the national level.

Moreover, instead of measuring overall banking innovation by including applications and practices of existing technologies, we also focus on only in-house innovation. To do so, following the literature related to patent-based technological innovation (see Chen et al. (2019), Jiang et al. (2022c), and Hasan et al. (2023)), we 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

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 level and improved performance. Although we include time-varying local economic variables to address this issue, unaddressed biases could remain. Second, banking innovation may be easier to promote performance and efficiency when the labor market frictions in high-tech fields decrease because of the larger increases in the national-level talents available.

observed in our sample are G06Q20, G06Q30, and G06Q40. These specific IPC codes encompass digital innovations that find application in payment systems, e-commerce platforms, and financial services, constituting 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 0.052% reduction of marginal net costs. The magnitudes are smaller compared to 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, down to the classification of in-house technological innovation.

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

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

NOTE: This table presents the results of regressing marginal net cost 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 levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

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 Table B.7 and Table 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 Appendix Table B.9 and B.10, we use the growth of the 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 cost, and brings 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 risk-weighted assets share.

Secondly, the construction of such 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 that are not related to employee training and potential efforts on innovative investment. This originates from either inefficient operations or the concerns that Chinese commercial banks are not able to translate technological expenses into productivity as sufficient as possible. To reconcile this issue, we reconstruct our measurement by only capitalizing 5% of general administrative expenses. The estimation results shown in Table B.11 and Table B.12 evidently support our main conclusions.

Finally, in Appendix Table B.13, we also check other performance and efficiency measures that are often used in the empirical banking literature such as Cost-to-Income Ratio, Income-over-Asset, Profit-over-Asset (see for example, Bikker and Haaf (2002) and Lin and Zhang (2009)). The results suggest that a higher initial level of banking innovation is associated with a higher income and profit with a large reduction in the Cost-to-Income ratio. Therefore, the overall banking innovation could bring banks to a higher operating efficiency level with a relative cost reduction.

In addition, since Chinese commercial banks exhibit striking heterogeneous features, it is also crucial to investigate which type of banks benefit the most from innovation on reducing marginal net costs. Appendix Table B.14 reveals that banks with lower risk exposure, larger size (especially top 5 banks, which are state banks), and higher profit benefit the most from investing in innovation to reduce their non-interest costs, therefore, a positive correlation between innovation investment efficiency and bank profitability and size.

To summarize, our empirical studies suggest that, by investing in innovation, banks reduce marginal non-interest related net expenses and may enhance their performance and efficiency. 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 ratio and risk-weighted assets share significantly increase.

Prior research has not fully elucidated the mechanisms through which innovative investment decisions can endogenously affect other investment activities (e.g., risk-taking behaviors) within banks. Furthermore, the implications of such investment decisions on social welfare and bank performance remain unclear, especially considering the heterogeneity of banks' innovation efficiency. Therefore, in the next section, we try to address these questions based on a general equilibrium model featuring banks' investment decisions on innovation which could reduce loan monitoring costs and fixed costs, as well as considering bank risk-taking subject to a capital adequacy ratio constraint.

3 Model

Motivated by the 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 the changes of technologies in the banking sector. 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 three types of agents: 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 $t = 0$. The deposit market is competitive, so a marginal deposit cost is r. There are two types of firms, one with safe technology and one with risky technology. Each firm borrows from the banks through bank loans. Lending to safe firms produces safe loans, and lending to risky firms produces risky loans. The bank decides the portfolio for these two types of loans. We assume that the risky loan market is monopolistic competition. So the bank can influence its price for risky firms, resulting in differential loan rates. The safe loan market is competitive, implying a homogeneous loan rate across borrowers. We assume the bank takes limited liability for the 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 to reduce the banks' 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 the 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. The profits and dividends are distributed to households for consumption. There are no financial frictions for the households. They face a competitive deposit market and are indifferent among deposits offered by heterogeneous banks. This implies $\beta(1 + r) = 1$, where r is the exogenous deposit rate in the deposit market.[14]

[14]One can interpret this setting as a small open economy with a risk-free interest rate determined in the international financial markets.

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 unit measure. All firms start without financial capital and rely on bank loan finance 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. Denote p^S as the loan price for a safe project that has to 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 firms' 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 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 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 as follows

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

With probability $1 - \chi$, $\chi \in (0, 1)$, the risky project will fail with zero revenue. With probability χ, the project is successful with a revenue of $\left(1 + A^R\right) f(l^R)$. 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

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

The above model setup implicitly assumes that banks can diversify idiosyncratic firm-level shocks, but the failure risk cannot be diversified.

The assumption of a monopolistic competition market for risky loans and a competitive market for safe loans is for the sake of simplicity. This implies that the risk-free rate is the same across different banks, and the risky loan rates charged by individual banks vary across banks.[15] 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, where banks compete over the amount of loans. Instead, we allow for both price and quantity competitions 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, etc. As we will see later, individual banks' optimal decisions will be important and influence the aggregate supply side of the loan market. Thus, 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 also suggests (e.g., Martinez-Miera and Repullo, 2010) that considering equilibrium project performance and loan performance may have important implications for banks' competition and risk-taking decisions.[16]

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 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 to reduce the non-interest expense/cost. In the second period, the investment outcomes are realized, and the cost takes place. The bank distributes the profit to the households

[15] 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.

[16] 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 the price elasticity and markups depend on market share (larger firms could charge even higher markups). In this way, we do not need to explicitly model the endogenous market structure and banks' dynamics; see Corbae and D'Erasmo (2021) for details along these lines.

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 $i(j) \geq 0$. The above setting implicitly assumes the bank can only obtain external finance through deposits.

The bank's cost structure consists of interest-related costs and non-interest expenses. The former cost is $(1 + p^S)l^S(j) + [1 + p^R(j)]l^R(j)$. 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 $e(j) + b(j)$. The above cost function reflects the idea that to achieve bank-wide innovation rate z, larger banks need to invest more in levels.[17] The elasticity of innovation rate $z(j)$ with respect to the investment rate, $\frac{i(j)}{e(j)+b(j)}$, is given by $1/\eta$. The cost function (8) is also consistent with the previous empirical finding that the R&D investment reduces the 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.

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

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 (see 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; and the parameter $\xi>0$ is required 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 $\mathbb{E}\left[\max\{\pi(j),0\}\right]$. Notice that 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 must have $\pi(j)>0$ when the risky project succeeds; otherwise, the bank's expected value, $\mathbb{E}\left[\max\{\pi(j),0\}\right]$, cannot be positive. Notice that banks are heterogeneous in the initial equity $e(j)$ and deposit $b(j)$. Thus, 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 deposit 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 $\mathbf{I}(j)$ 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 $\mathbf{I}(j)$ depends on the individual bank's state. We can rewrite the bank's expected value as

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

3.3.2 Bank's optimal decisions

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

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

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

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 innovate rate $z(j)$ by $\frac{\partial z(j)}{\partial i(j)}$, which further help to reduce the non-interest expenses of $c_L\left[l^S(j) + l^R(j)\right] + c_F$. The expected reduction in the non-interest expenses depends on the state of the risky project, which is characterized by $\chi + (1-\chi)\mathbf{I}(j)$.

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

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

The L.H.S. reflects the marginal cost of allocating safe loans, where the term $\phi(j)\,\xi$ 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 risk loan $l^R(j)$ satisfies

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

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 $\frac{1}{\beta\chi}\frac{\epsilon}{\epsilon-1}\phi\left(j\right)\xi\left(\psi-1\right)$ 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 ($\phi\left(j\right) = 0$) or the risky loan shares a same risk-weight ($\psi = 1$), the second premium term vanishes. The third term $\frac{1}{\chi}\frac{\epsilon}{\epsilon-1}\left(1+p^S\right)(1-\chi)\mathbf{I}\left(j\right)$ reflects the risk premium because the risky loan may induce bankruptcy.

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

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

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

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

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

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

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 the 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 the substitution effects.

When the CAR constraint becomes effective, i.e., $\phi(j) > 0$, a tightening of CAR constraint implies $\phi(j)$ increases. Equation (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 risky loans. The above 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 the 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 Define the aggregate safe loans as $l^S = \int_0^1 l^S(j)\, dj$. The initial distribution for individual bank's equity and deposit $\{e(j), b(j)\}$ are exogenously given. 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 the 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 the risky loans, the price and quantity of composite loan, $\{p^R, l^R\}$, are determined by the price indexation equation (5) and the 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, $(1 + r) \int_{j=0}^{1} b_0(j) dj$. 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, the 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 write the total welfare as

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

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 the model parameters. For the 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 $\beta = 1/(1+r)$. For the firm's production function, $f(l)$, we assume the safe technology is a constant return to scale, i.e., $f^S(l) = l$. While for risky technology, we assume it is strictly concave, following $f^R(l) = l^\alpha$, where α is set to be 0.5, so 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 the 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 $A^R = 14\%$.[18] The parameter η that governs the elasticity of innovation rate for the successful projects to R&D investment. To our best knowledge, there are few direct measures in the literature, and we do not have good empirical counterparts in our context either. Thus, we borrow the 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.[19] 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. These banks need to disclose their internal assessments of CAR, the procedures,

[18] 14% is also quite close to China's unsecured credit card interest rates. For example, the data sources are www.Bankrate.com and the report from Bloomberg.

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

and the risk weighting for different types of assets (see more discussions in Li et al. (2022) for a regulation policy change around 2014). 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.

Lastly, σ is assumed to be 0.20, or there will be an additional 20% deadweight loss for the whole society if there are bank bailouts. This value is relatively conservative (see some examples in Hellmann et al. (2000)). In the exercises below, we will experiment with different values and confirm our main results.

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

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

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

$$\log(\omega) = \rho_{e,\omega} \log(e_0) + \mathcal{N}(\mu_\omega, \sigma_\omega^2).$$

In this way, we have seven parameters regarding the initial distributions that we need to pin 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 part.

We choose a rich set of relevant model moments and data moments to best estimate the parameters. Intuitively, for the parameters related to initial distributions, the following moments can provide closely related information for e_0 and b_0: the standard deviations for log equity and for log assets; the average and the standard deviation for banks' leverage, and the correlation between equity and bank leverage. For e_0 and ω, the correlation between intangible investment and bank equity, the average and the standard deviation of intangible investment (scaled by bank revenue), can provide close information on $\rho_{e,\omega}$, μ_ω, and σ_ω. For ϵ, m, and c_F, they will affect the model's implied markup of marginal prices over marginal costs across different banks, 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]

[20]Markup in the model is computed as the total expected payments over total expected total variable cost; that is,

$$\frac{E_\chi\left[l_0^S(1+p^S) + l_0^R(1+p^R(j))\right]}{b_0 r + E_\chi\left(l_0^S + l_0^R\right) m(1-z)} - 1.$$

That is, it is defined as close to the empirical counterpart as possible.

Table 6: Endogenously Estimated Parameters

Parameter	Description	Value
χ	Prob. of Project Succeed	0.898
m	Non-interest Cost per Loan	0.017
c_F	Non-interest Fixed Cost	0.355
σ_e	Std. for $\log(e_0)$	1.415
$\rho_{e,L}$	Corr. between $\log(e_0)$ 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 $\log(e_0)$ 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

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

5 Quantitative Exercises

In this section, we leverage on the quantitative model and further explore the implications when banks endogenously choose optimal innovation activities. In particular, we would like to know how banks' other investment activities (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 the innovation activities across different banks. We divide banks into five quintile based on their innovation efficiency, ω. For each group, we then plot in the figure 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), R&D innovation rates (z) in panel (c). Higher individual innovation efficiency is directly associated with higher R&D investment in the model; for the absolute levels of R&D investment, group Q5 has about 10 times higher than group Q1. We can also see this from panel (c), where innovation rates z are directly impacted by R&D investment. Since the initial distribution of assets is positively

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

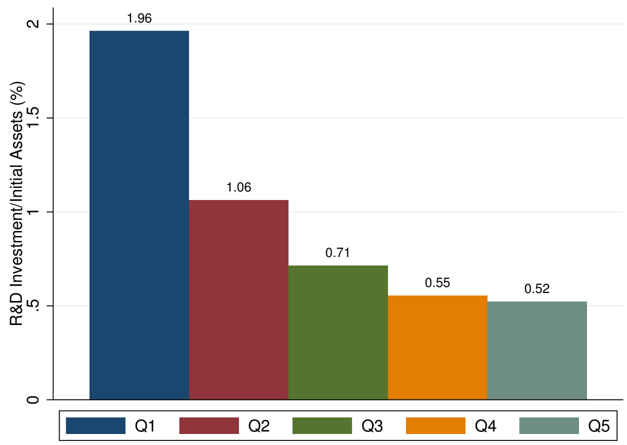
correlated with ω, banks with higher ω tend to be larger and have higher revenue. Thus, for the ratios, they decrease with ω, as shown in panel (a) and (b).

Quantitatively, for banks with the lowest quintile of ω, on average 1.96% of the initial assets are invested for R&D, but 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 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 the effects of R&D investment are economically important.

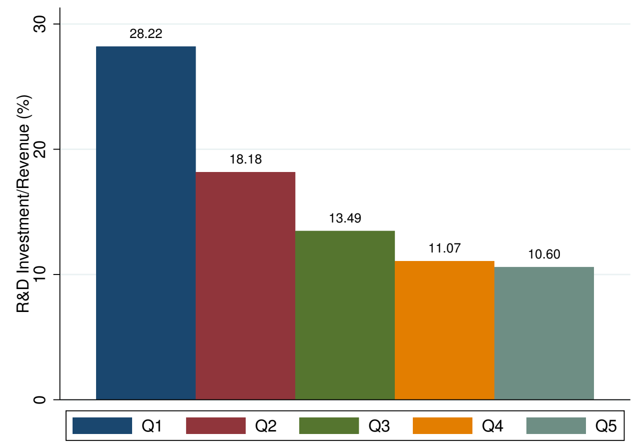
Next, when we study the impacts of innovations on banks' investments, loan decisions and overall social welfare, it is helpful to look at banks' risk-taking behaviors. In Figure 4 panel (a), we plot the average bankruptcy probability across banks within each group. Clearly, the average probability decreases with innovation efficiency. This is mostly driven by the fact that it is more likely for banks with smaller initial capital to have negative equity values in the second period as there are both fixed and variable loan issuance costs; 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 the average bankruptcy probability decreases with innovation efficiency.

Figure 3: The Cross-Sectional Distribution for R&D Investment and Innovation; By ω Groups

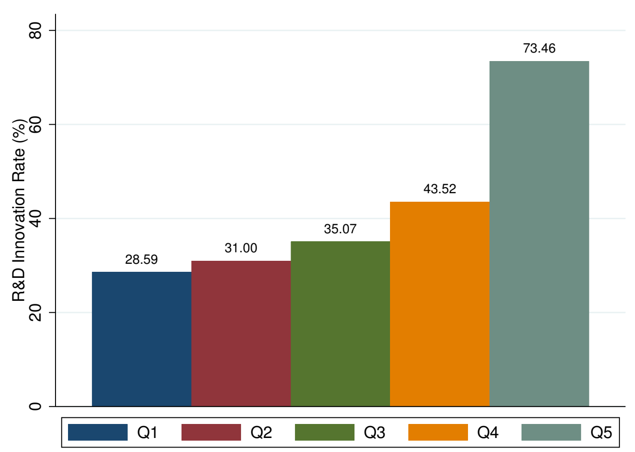
(a) R&D investment/Assets



(b) R&D investment/Revenue



(c) R&D innovation rates

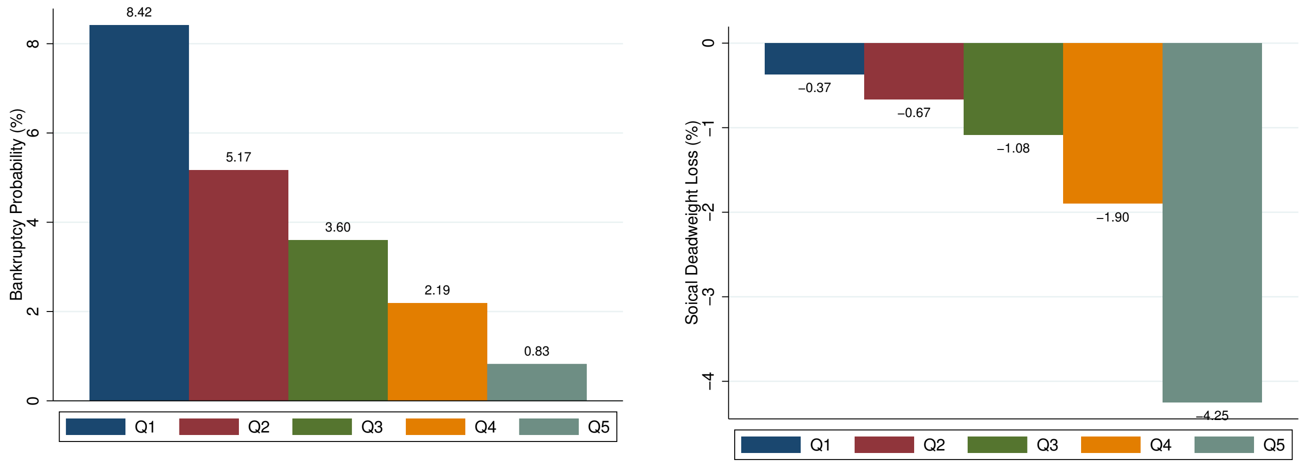


In panel (b) of Figure 4, we compute the average social deadweight loss conditional on bankruptcy. That is, in the event of bankruptcy, the size of social deadweight loss (proportional to the value of negative equities), however, is increasing with innovation efficiency. This is because big banks, with higher ω, also have larger variable costs to repay (from the part of ml_0^R), simply because these banks issue a larger amount of risky loans. The fixed cost part is the same for all 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%; on the other hand, for the size of loss conditional bankruptcy, the numbers have different patterns and they are 0.37 vs. 4.25 (the economy's total initial assets is normalized to 1). These characteristics from the cross-sectional distribution suggest that banks' innovation may have important impacts on risk-taking activities and consequently on social welfare. We further explore these below.

Figure 4: Bankruptcy Probability and Social Deadweight Loss; By ω Groups

(a) Bankruptcy probability

(b) Social deadweight loss: averages conditional on bankruptcy



5.2 The Impact of Aggregate Banking Technology Development

Next, we consider aggregate innovation technology progress so that all banks' innovation efficiency increases. That is, all ω increases. This can be interpreted as some favorable aggregate technology development for banks' R&D, such as FinTech development, new technologies for monitoring and managing loans, new information technologies such as high-performance computation and more efficient storage methods, and so on.

When the aggregate innovation efficiency increases from the benchmark to about 20% higher, in Figure 5, we first see that the average bankruptcy probability across the economy increases with aggregate efficiency, the aggregate share for risky loans also increases (computed as aggregate risky loans relative to all loans). Quantitatively, when aggregate efficiency increases by 20%, average bankruptcy probability increases by about 2% and aggregate share for risky loans by about 1%. The increasing pattern is also confirmed when we look at individual banks by groups (see, for example, the Figures D.4 and D.5 in the Appendix, when banks are grouped by individual ω).

Why would higher innovation efficiency increase risky loans? This could be explained from different perspectives. (1) since the bank faces a portfolio choice problem, it has three different investment options: R&D investment, lending to safe loans and lending to risky loans. In an optimal choice, the bank will try its best to balance the returns from different options: when the return from R&D investment becomes higher, it has incentives to re-adjust its portfolios; as a result, the bank will invest more into risky assets on the margin since it offers a relatively higher mean return. (2) We can also explore the first-order conditions to have more intuition:

$$
\begin{aligned}
\text{F.o.c for R\&D:} \quad \mu_0 &= \beta \frac{\partial z}{\partial i}(ml_0 + c_F)E_\chi \\
\text{F.o.c for } l_0^R\text{:} \quad \mu_0 + \phi_0 \xi \Psi &= \beta \left(1 + p^R(j)\frac{\epsilon - 1}{\epsilon}\right)\chi - \beta m(1-z)E_\chi.
\end{aligned}
$$

When aggregate efficiency is higher, R&D investment has higher efficiency, which effectively lowers the required resources for R&D investment if holding the marginal return not changing; in turn, the saved resource can be allocated into other investments, and typically into risky assets. Technically, the shadow value of a current dollar, μ_0, would adjust in the thought experiment. (3) Lastly, we could also inspect the first order condition for l_0^R investment: since z values in the next period will be endogenously higher due to higher aggregate efficiency (even if the R&D investment is not changing), this effectively boosts the return for risky assets (holding E_χ not changing). This force tends to increase risky investments. At the same time, the bank's bankruptcy probability will be increased (E_χ decreases), and this counterforce tends to lower levels of risky investment. In combination, it is typically the first one that dominates, and therefore innovation encourages more risk-taking.

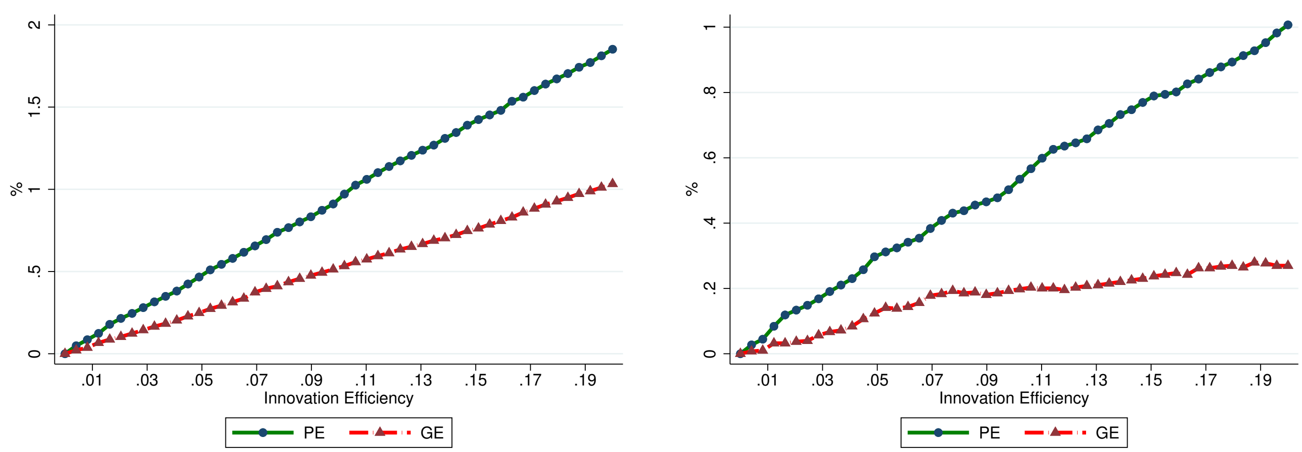
Equilibrium effects. In the market for risky loans, there is imperfect competition across banks. If some individual banks would like to lend more in risky loans, they have to compete in the loan market and offer slightly lower loan prices, which tends to lower the return of loans. Therefore, in general equilibrium, banks tend to invest less in risky assets than in partial equilibrium. This is evident from Figure 5. Quantitatively, the equilibrium effects are important and about half of the changes are due to general equilibrium in the loan market.

Having discussed the impacts of aggregate innovation efficiency on individual banks, we then assess the overall welfare implications. In Figure 6, we compute the changes for total social welfare (scaled by total initial assets, in panel (a)); we also plot the changes for two important welfare components, total loan issuance costs in panel (b) (roughly accounts for 1.1% of total welfare), and total social deadweight loss in panel (c) (roughly accounts for 0.35% of total welfare). We find as the aggregate efficiency increases, the overall social welfare increases, roughly by 0.15% when the efficiency is higher by 20%. This is mainly driven by the fact that the loan issuance cost is reduced since banks can better utilize R&D investment to facilitate loan issuance.

However, we also see that the total social deadweight loss actually increases: this is because individual banks tend to invest more into risky loans in the face of better aggregate technology, as explained above. As banks have deposit insurance, this is the cost for moral hazard and it increases with higher aggregate innovation efficiency. At the same time, we should note that since loan issuance costs (both fixed costs and variable costs) are reduced, this will lower the

Figure 5: The Impacts of Aggregate Technology on Banks

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



bank's loss conditional on bankruptcy. Overall, the loan issuance costs channel still dominates and we see the total social welfare increases.

In short summary, we find that when the aggregate innovation efficiency increases, total social welfare increases as the financial intermediation costs can be reduced, but at the same time, we also see banks will increase their moral hazard activity and increases the social deadweight loss. This is a new channel for how innovation impacts the banking sector and a new mechanism in the literature.

5.3 Policy Implications: The Impact Of R&D Investment Subsidizing Policy

Closely related to the previous exercise, it is natural to ask what would be the impacts of government policies regarding R&D investment, for example, tax credit subsidy policy, a widely adopted fiscal policy across countries. In this section, we consider this R&D investment subsidy policy. In particular, assume the government can subsidize a fraction, ι, of R&D investment for each bank. That is, the budget constraint now becomes

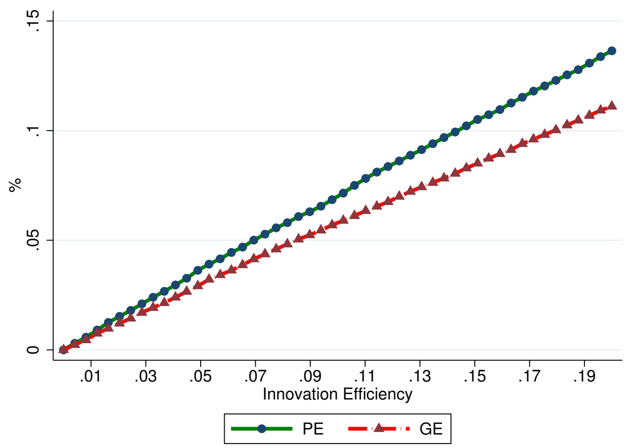
$$e_0 + b_0 - l_0 - i(1-\iota) \geq 0,$$

and all other constraints for the bank need not to be changed. Also, the government will use a lump-sum tax from the representative household. Thus, when computing the total social welfare, we also need to subtract the amount of tax credit, $\beta \int_{j=0}^{1} \{i\iota\}\, dj$, from the total welfare.

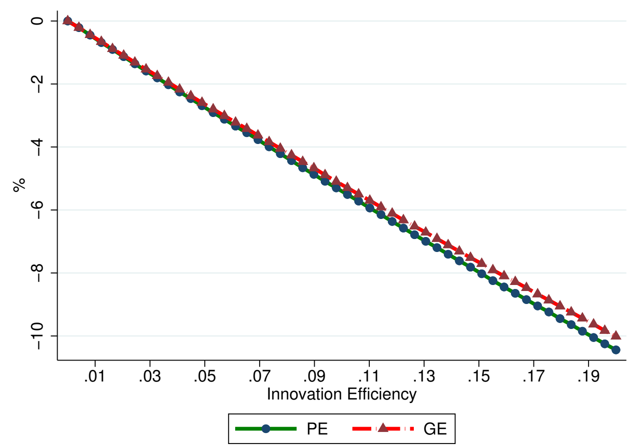
In Table 8, we consider $\iota = 0.20$ and report the results on aggregate variables as well as individual banks' characteristics. When we have tax subsidies, the overall effect is very similar

Figure 6: The impacts of Aggregate Technology Change on Social welfare

(a) Total Social welfare



(b) Loan issuance costs



(c) Social deadweight loss

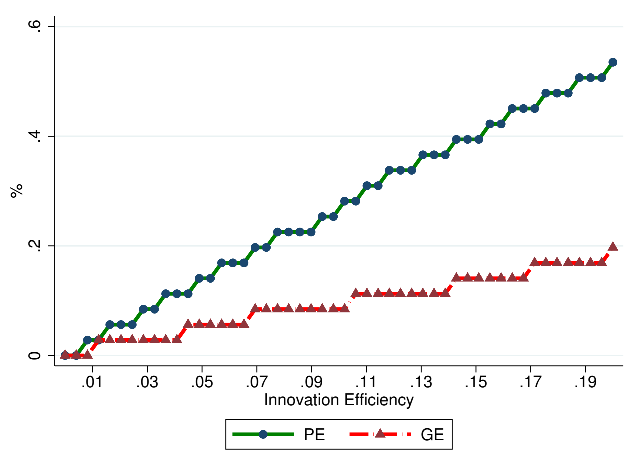


Table 8: The Impacts of R&D Tax Credit

	Benchmark	With credit	% 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

to the case when we have a higher aggregate innovation efficiency. 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. In the optimal solution, the bank must balance different investment options; therefore, it also shifts to more risky loans, as the average return from loans can be increased. Alternatively, to achieve the same rate of return across different investment options, now the bank just needs fewer resources; in turn, the effectively "saved" additional resources can be allocated for more risky loans, and this is without violating the CAR constraint.

Quantitatively, Table 8 reports that the total loan issuance costs of the economy can be reduced by about 12%; that is, banks are encouraged to invest more in R&D and the resulting innovations on average can reduce loan monitoring/issuances costs. For example, banks with the highest level of innovation efficiency will increase their R&D by almost 32% (scaled by assets). The average innovation rate in the next period also increases by about 9.8%. However, the social deadweight loss also increases by about 0.25%, since banks now invest more in risky assets. We can also see this from the share of risky loans by groups (Q1 and Q5). The average bankruptcy probability for banks with the lowest level of innovation efficiency will increase by about 0.35%. This fact should be read together with the fact that, conditional on being bankrupt, the average size of deadweight loss will become smaller, due to the increased R&D investment and increased innovation rates. Quantitatively, the total effect on social welfare actually is not that large, only about 0.03%. Thus, when the government considers tax credit subsidy policy for the banking sector, it is important to analyze the consequences carefully, and especially, one needs to cautiously take banks' risk taking incentives into account.

5.4 Policy Implications: How Does Innovation Change When CAR Increases?

Previous analysis shows that the bank's innovation activity may have important interaction and dynamics with the bank's risk-taking behavior. For banks' risky investment in loans, it is typically subject to government regulations (CAR). As another exercise, here we consider an exogenous increase in CAR and investigate the impacts. In particular, we increase the CAR from our benchmark value 12% to 15%. That is, $\frac{e_0}{l_0^S+\Psi l_0^R} \geq \xi$ is constrained with higher ξ.[21]

Table 9 compares the results with the benchmark economy. Overall we see the total Social welfare increases with a higher capital requirement. There are mainly two counter forces behind this: first, banks on average will have fewer social deadweight losses after the CAR is higher. This happens since banks are required to have less risky loans holding everything else constant. Second, the economy's total loan issuance costs increases, since the innovation is reduced and also, as the economy relies more on safe loans and the units of safe loans increase more than the decrease in risky loans. Quantitatively, both channels are important for the 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 can also inspect the changes for banks by groups, we find that there are heterogeneous responses. Table 9 shows for banks with large ω and large capital will have smaller risky shares, smaller bankruptcy probability and a smaller loss conditional on bankruptcy. In addition, these banks optimally allocate more initial funds to safe loans to satisfy higher capital requirements, and as a result, even for R&D investment it also has to be reduced slightly (by about 0.8%). For banks with lower ω and lower initial capital, the responses are similar in terms of risky loans, but for R&D investment it is reduced more. Since banks' revenue decrease, the ratio of R&D investment to revenue may differ across banks.

Lastly, for the policy implications, however, it should be interpreted cautiously. In our economy, as we highlight the impacts of bank innovation and its interaction with risk-taking and moral hazard behaviors, we deliberately keep the model economy simple and transparent. However, this is not without prices. The initial distributions of bank capital and deposit are exogenous and fixed. Thus, there are no endogenous dynamics of bank capital, leverage and risky investments over time when the government regulation on CAR changes; also, banks' entry and exit dynamics in the economy may also change when the aggregate environment changes. It is interesting and important for future studies to further explore all these details and go beyond the scope of this paper.

[21] For comparison across experiments, since we change ξ, we select those banks that have positive present values (with initial (e_0, b_0)) under both experiments.

Table 9: Increasing 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

6 Concluding Remarks

Over the past decades, banking innovation has drastically changed traditional bank lending business models. However, there is limited research on the detailed channels of the impacts and, consequently, the evaluations for the aggregate welfare impacts. In this paper, we provide a comprehensive study of banks' innovative investment, which we regard as banks' investment to enhance their efficiency and profitability 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 profitability, primarily reducing non-interest costs but not so much on deposit costs. We also show that banking innovation may unintended increase bank risk-taking behaviors. These findings are pretty robust under a battery of robustness checks.

In a novel quantitative model, banks have heterogeneous capital, decide their investment in innovation and risky lending, face regulations on the capital requirement, and have limited liability. Improving aggregate new technology can reduce financial intermediation costs and social deadweight loss; however, it will also change the 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 further questions. For instance, how does endogenous banking innovation transform the credit market allocation among shadow banking and traditional banking sector? How does banking innovation affect banks' systemic risks and monetary policy transmission?

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., and Kerr, W. (2018). Innovation, reallocation, and growth. American Economic Review, 108(11):3450–91.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. Journal of political economy, 128(6):2188–2244.

Aghion, P., Bergeaud, A., and Van Reenen, J. (2021). The impact of regulation on innovation. Technical report, National Bureau of Economic Research.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. Econometrica, 60(2):323–351.

Ahnert, T., Doerr, S., Pierri, M. N., and Timmer, M. Y. (2021). Does IT help? Information technology in banking and entrepreneurship. Number 17335. International Monetary Fund.

Akcigit, U. and Kerr, W. R. (2018). Growth through heterogeneous innovations. Journal of Political Economy, 126(4):1374–1443.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. The Quarterly journal of economics, 118(4):1279–1333.

Babus, A., Marzani, M., and Moreira, S. (2023). Innovation for innovators: The financing of intangibles. In AEA Papers and Proceedings, volume 113, pages 268–73. American Economic Association.

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. The quarterly journal of Economics, 122(4):1721–1758.

Beck, T., Chen, T., Lin, C., and Song, F. M. (2016). Financial innovation: The bright and the dark sides. Journal of Banking & Finance, 72:28–51.

Beck, T. and Levine, R. (2018). Handbook of finance and development. Edward Elgar Publishing.

Belo, F., Gala, V. D., Salomao, J., and Vitorino, M. A. (2022). Decomposing firm value. Journal of Financial Economics, 143(2):619–639.

Berg, T., Burg, V., Gombović, A., and Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. The Review of Financial Studies, 33(7):2845–2897.

Berger, A. N. (2003). The economic effects of technological progress: Evidence from the banking industry. Journal of Money, credit and Banking, pages 141–176.

Berger, A. N., Klapper, L. F., and Turk-Ariss, R. (2008). Bank competition and financial stability. Journal of Financial Services Research, 2(35):99–118.

Bikker, J. A. and Haaf, K. (2002). Competition, concentration and their relationship: An empirical analysis of the banking industry. Journal of banking & finance, 26(11):2191–2214.

Björkegren, D. and Grissen, D. (2020). Behavior revealed in mobile phone usage predicts credit repayment. The World Bank Economic Review, 34(3):618–634.

Boyd, J. H. and De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. The Journal of finance, 60(3):1329–1343.

Branzoli, N., Rainone, E., and Supino, I. (2021). The role of banks' technology adoption in credit markets during the pandemic. Available at SSRN 3878254.

Branzoli, N., Rainone, E., and Supino, I. (2023). The role of banks' technology adoption in credit markets during the pandemic. Bank of Italy Temi di Discussione (Working Paper) No, 1406.

Buchak, G., Matvos, G., Piskorski, T., and Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of financial economics, 130(3):453–483.

Caragea, D., Chen, M., Cojoianu, T., Dobri, M., Glandt, K., and Mihaila, G. (2020). Identifying fintech innovations using bert. In 2020 IEEE International Conference on Big Data (Big Data), pages 1117–1126. IEEE.

Chen, K., Xiao, Y., and Zha, T. (2022). China's monetary transmission and systemic risk: A role of interbank bond markets.

Chen, M. A., Wu, Q., and Yang, B. (2019). How valuable is fintech innovation? The Review of Financial Studies, 32(5):2062–2106.

Cojoianu, T., Peia, O., Caragea, D., Hoepner, A., Dobri, M., and Romelli, D. (2023). Competition and innovation in the financial sector: Evidence from the rise of fintech start-ups. Journal of Financial Services Research.

Cong, L. W., Gao, H., Ponticelli, J., and Yang, X. (2019). Credit allocation under economic stimulus: Evidence from china. The Review of Financial Studies, 32(9):3412–3460.

Corbae, D. and D'Erasmo, P. (2021). Capital buffers in a quantitative model of banking industry dynamics. Econometrica, 89(6):2975–3023.

Corrado, C., Haskel, J., Iommi, M., and Jona-Lasinio, C. (2020). Intangible capital, innovation, and productivity à la jorgenson evidence from europe and the united states. In Measuring Economic Growth and Productivity, pages 363–385. Elsevier.

Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2022). Intangible capital and modern economies. Journal of Economic Perspectives, 36(3):3–28.

Crespi, G., Criscuolo, C., and Haskel, J. (2007). Information technology, organisational change and productivity.

De Fiore, F., Gambacorta, L., and Manea, C. (2023). Big techs and the credit channel of monetary policy.

De Nicolo, G., Presbitero, A., Rebucci, A., and Zhang, G. (2021). Technology adoption, market structure, and the cost of bank intermediation. Johns Hopkins Carey Business School Research Paper, (21-12).

De Ridder, M. (2021). Market power and innovation in the intangible economy. London School of Economics, Department of Economics Working Paper.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. The review of economic studies, 51(3):393–414.

Ewens, M., Peters, R. H., and Wang, S. (2019). Measuring intangible capital with market prices. Technical report, National Bureau of Economic Research.

Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., and Zbinden, P. (2019). Bigtech and the changing structure of financial intermediation. Economic Policy, 34(100):761–799.

Fu, J. and Mishra, M. (2022). Fintech in the time of covid- 19: Technological adoption during crises. Journal of Financial Intermediation, 50:100945.

Fuster, A., Plosser, M., Schnabl, P., and Vickery, J. (2019). The role of technology in mortgage lending. The Review of Financial Studies, 32(5):1854–1899.

Gao, H., Ru, H., Townsend, R., and Yang, X. (2019). Rise of bank competition: Evidence from banking deregulation in china. Technical report, National Bureau of Economic Research.

Hasan, I., Li, X., and Takalo, T. (2023). Technological innovation and the bank lending channel of monetary policy transmission. Available at SSRN 3928813.

Hellmann, T. F., Murdock, K. C., and Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? American economic review, 90(1):147–165.

Huang, Y., Li, X., Qiu, H., and Yu, C. (2023). Bigtech credit and monetary policy transmission: Micro-level evidence from china.

Jiang, E. X., Yu, G. Y., and Zhang, J. (2022a). Bank competition amid digital disruption: Implications for financial inclusion. Available at SSRN 4178420.

Jiang, S., He, Z., Yin, X., and Xu, D. (2022b). Investing in lending technology: It spending in banking. Available at SSRN 3936084.

Jiang, W., Tang, Y., Xiao, R. J., and Yao, V. (2022c). Surviving the fintech disruption. Technical report, National Bureau of Economic Research.

Jones, C. I. (2011). Intermediate goods and weak links in the theory of economic development. American Economic Journal: Macroeconomics, 3(2):1–28.

Klenow, P. J. and Willis, J. L. (2016). Real rigidities and nominal price changes. Economica, 83(331):443–472.

Klette, T. J. and Kortum, S. (2004). Innovating firms and aggregate innovation. Journal of political economy, 112(5):986–1018.

Kogan, L. and Papanikolaou, D. (2019). Technological innovation, intangible capital, and asset prices. Annual Review of Financial Economics, 11:221–242.

Kwan, A., Lin, C., Pursiainen, V., and Tai, M. (2021). Stress testing banks' digital capabilities: Evidence from the covid-19 pandemic. Available at SSRN 3694288.

Lerner, J. (2006). The new new financial thing: The origins of financial innovations. Journal of Financial Economics, 79(2):223–255.

Li, X., Liu, Z., Peng, Y., and Xu, Z. (2022). Bank risk-taking and monetary policy transmission: Evidence from china. Federal Reserve Bank of San Francisco Working Paper.

Lin, X. and Zhang, Y. (2009). Bank ownership reform and bank performance in china. Journal of Banking & Finance, 33(1):20–29.

Liu, L., Lu, G., and Xiong, W. (2022). The big tech lending model. Technical report, National Bureau of Economic Research.

Martinez-Miera, D. and Repullo, R. (2010). Does competition reduce the risk of bank failure? The Review of Financial Studies, 23(10):3638–3664.

Modi, K., Pierri, N., Timmer, Y., and Peria, M. S. M. (2022). The anatomy of banks' it investments: Drivers and implications. IMF Working Papers, 2022(244).

Peters, R. H. and Taylor, L. A. (2017). Intangible capital and the investment-q relation. Journal of Financial Economics, 123(2):251–272.

Philippon, T. (2010). Financiers versus engineers: Should the financial sector be taxed or subsidized? American Economic Journal: Macroeconomics, 2(3):158–82.

Philippon, T. (2015). Has the us finance industry become less efficient? on the theory and measurement of financial intermediation. American Economic Review, 105(4):1408–1438.

Philippon, T. (2016). The fintech opportunity. Technical report, National Bureau of Economic Research.

Pierri, N. and Timmer, Y. (2022). The importance of technology in banking during a crisis. Journal of Monetary Economics, 128:88–104.

Romer, P. M. (1990). Endogenous technological change. Journal of political Economy, 98(5, Part 2):S71–S102.

Song, Z., Storesletten, K., and Zilibotti, F. (2011). Growing like china. American economic review, 101(1):196–233.

Thakor, A. V. (2020). Fintech and banking: What do we know? Journal of Financial Intermediation, 41:100833.

Vives, X. (2019). Digital disruption in banking. Annual Review of Financial Economics, 11:243–272.

Vives, X. and Ye, Z. (2023). Information technology and lender competition. IESE Business School Working Paper.

Zhao, Y., Goodell, J. W., Wang, Y., and Abedin, M. Z. (2023). Fintech, macroprudential policies and bank risk: Evidence from china. International Review of Financial Analysis, 87:102648.

Appendix

A Data Appendix

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

Innovation has become a critical component of financial business in the banking sector, which helps banks increase efficiency, promote lending and attract deposits, therefore, enhance their market power. For instance, employees training programs improve organizational efficiency. Newly invented software and advanced equipments enable banks to reduce their marginal costs and obtain higher profits. Adopting information technology (IT) and Big data may transform bank business from branch-reliant to online applications. It also allows bank to provide more personalized services and perhaps reduce their marginal costs (such as AI customer service and automation).

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's information technology (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 spending as a subchapter termed "FinTech Investment and Innovation Progress" in the annual reports.[22] Besides, banks explicitly describe their efforts in innovations not only with the scope of IT adoption, but also including 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 measurement of banking innovation by capitalizing banks' investments in innovation.

Specifically, following Peters and Taylor (2017) and Belo et al. (2022), we use the perpetual inventory method to capitalize 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 bank's on-balance sheet intangible assets.[23] 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))

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

[22] China's commercial banks largely invested in IT adoptions. IT expenses reported by State banks all exceed 10 billions CNY by 2021. Bank IT expenses include business system developments, management information system, software developments, retail services labels, and business models. Business system developments and management information system are two dominant parts of the expenses. The first one contains settlement systems, online banking systems, management information system and 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 to perform risk management and loan originations.

[23] 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

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

in which $\{o, k\}$ 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 check, 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. 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.

The patent applications are collected for each bank from Shanghai Intellectual Property Information Service Platform. We exclude patents that not related to bank business improvement such as design patents. Based on the International Patent Classification (IPC) codes, the remaining patent applications are mostly belong to: G06Q, this IPC code covers data processing systems or technological methods which are usually adapted for the administrative, commercial, financial, managerial, supervisory, or forecasting purposes. The most frequent subcategories of IPC code 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 FinTech applications used in banking sector (see Chen et al. (2019)).

Moreover, following the literature, we also classify patent documents into different categories of FinTech innovations, and construct measures of FinTech innovation, the results are still consistent.[24]

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:

[24] Recent literature aims to measure FinTech 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 FinTech 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) follows 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, in which the Fintech patents are classified following Chen et al. (2019). We follow this strand of literature, and categorize patents into FinTech-related patents based on the International Patent Classification (IPC) and Cooperative Patent Classification (CPC), which are assigned by the Intellectual Properties Offices to distinguish patent categories. We also complement the sample by adding patents whose title or abstract contains FinTech-related keywords provided by Chen et al. (2019).

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

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.

Existing literature argues that banking innovation may facilitate lending by charging a higher rate, or attract deposit 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.

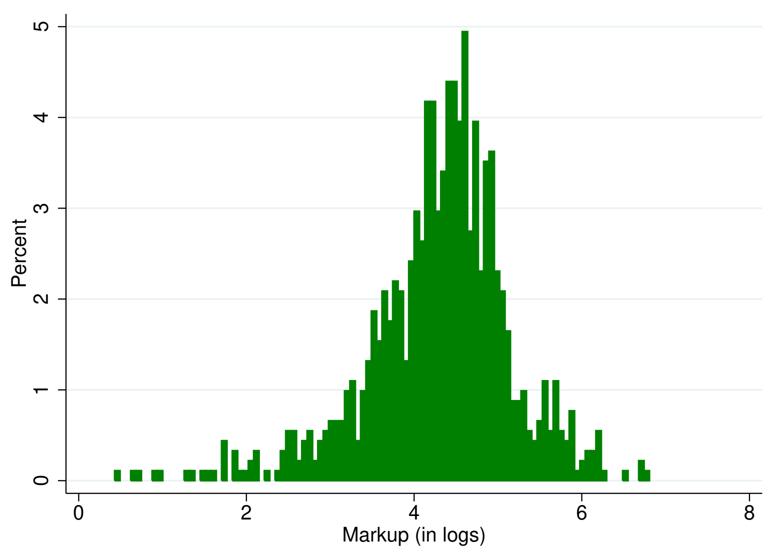
Table A.1 below presents the moments of loan markup related to quantiles of bank size (measured by bank total assets). Figure A.1 plots the distribution of loan markups in our sample. The loan markups are positively correlated with bank size.

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: The last six rows describe the average loan markup based on bank size. For example, the average loan markup is 502.42 for those banks whose total assets ranked Top 1%.

Figure A.1: Distribution of Markups



The main variables are defined in Table A.2. The data set covers bank-level information on bank loans and deposits and other balance-sheet variables, constructed 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. Moreover, we construct the instrument variable by including both graduates with Master of Science and Master of Science in Engineering, reported by the Ministry of Education in China. This measurement is almost equivalent to the definition of STEM (Science, Technology, Engineering, and Mathematics).[25]

[25]We construct IV based on initial exposure instead of a yearly rolling window. This is because, in our unbalanced

Table A.2: Main Variables' Definition and Construction

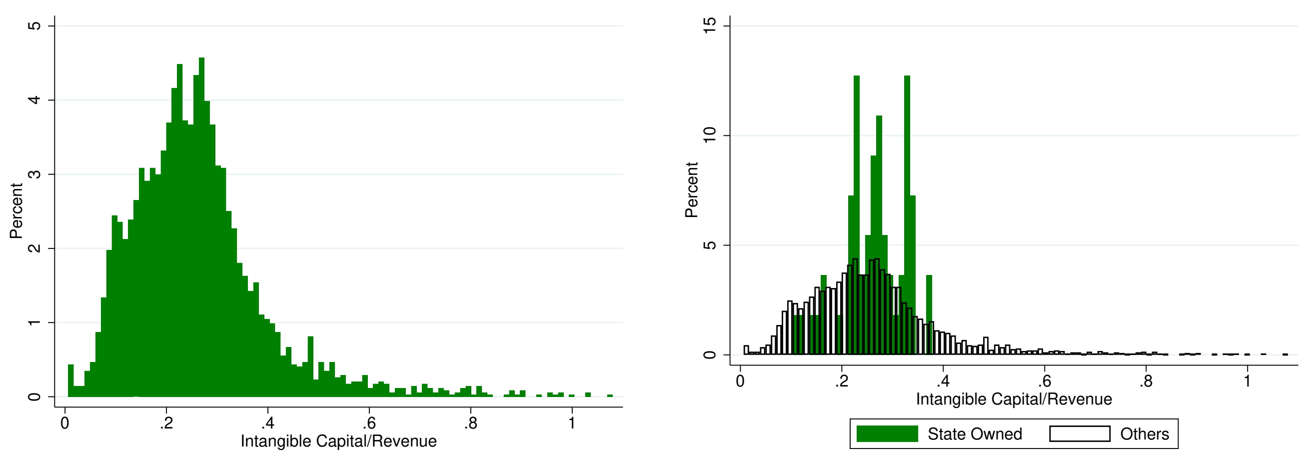
Variables	Definitions
Banking Innovation	Capitalized Overall Investments in Innovation or Number of Total Patents
Marginal Net Expenses	Marginal Non-Interest Expense - Marginal Non-Interest Income
Loan Markup	Interest Return on Loans / (Cost of Funds + Marginal Net Expenses) -1
Interest Return on Loans	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: in the main context, we measure banking innovation by capitalized overall investment in innovation in spirit of Peters and Taylor (2017). We also compute the number of patents classified as technological innovations as an alternative measure.

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

Figure A.2: Distribution of Intangible Capital

(a) All Banks (b) By Bank types



panel dataset, only a few major banks have a long-spanned time horizon and update their graduate employee share annually. Conversely, most banks have limited periods and data available only on their initial graduate employee share.

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

	mean	sd	p50	p25	p75
Panel A: State Banks					
Intangible Capital (log)	6.894	0.765	7.117	6.414	7.480
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
SRISK (10bn RMB)	53.289	32.465	49.743	26.371	68.215
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
Observations	75				
Panel B: Nonstate Banks					
Intangible Capital (log)	1.645	1.304	1.386	0.596	2.358
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
SRISK (10bn RMB)	7.855	10.734	3.421	1.130	10.440
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
Observations	4870				

Figure A.3: Aggregate Level of Loan Markup and its Components

NOTE: The four panels are organized as follows. The top left panel: the average loan markup; the top right panel: the interest return on loans from the previous year; the bottom left panel: the cost of funds measured as interest paid to deposits and central bank over total deposits and central bank borrowings; the bottom right panel: marginal net expenses derived from trans-log function, computed following empirical banking literature. We demonstrate the aggregate variables in four ways: simple average, weighted by assets, state-owned banks (top 5) only, and top 10 banks only. 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 Appendix Tables for Robustness Checks

This subsection contains the Appendix Tables for robustness checks as described in Section 2.4.

Table B.4: Effects of Banking Innovation on Marginal Net Expenses: First Stage

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

NOTE: The instrument variable is constructed based on bank-level initial IT employee share multiplied with national-level STEM growth rate, which denotes the initial exposure of individual bank to aggregate-level growth rate.

Additional Results To investigate which banks benefit the most from innovation technology on reducing non-interest costs. We check the heterogeneous impact of intangible capital on non-interest net expenses. Following Li et al. (2022), we classify risky bank groups by defining the dummy variable $\mathbb{I}^{\text{High NPL}}$, which equals one if bank i's average share of NPL is above the median and zero otherwise. Moreover, we capture high markup group, large asset size group by defining $\mathbb{I}^{\text{High Markup}}$, $\mathbb{I}^{\text{High Size}}$, which equal to one if bank i's markup or size exceeds the median at year t, and zero otherwise. We also construct state-owned dummy variable if banks are the top 5 largest banks (state banks), $\mathbb{I}^{\text{State-owned}}$. We regress the basic specification by including the interacted term with dummy variables.

Appendix Table B.14 shows that for banks with better performance and profitability, bigger size, and especially state-owned (also Top 5), banking innovation results in a larger effect of reducing marginal cost.

Table B.5: Effects of Banking Innovation on Loan Markups: IV

	Log(Markup+1)		Int. Ret. Loans		Cost of Funds		Mg. Non. Net Expenses	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Intangible Capital (log)	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)
Observations	715	715	715	715	715	715	715	715
R^2	0.772	0.072	0.897	0.126	0.723	0.228	0.710	0.344
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: For each dependent variable, we compare the estimation results between OLS and 2SLS with instrument variable 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 levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

Table B.6: Effects of Banking Innovation on Risk-taking: using IV

	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)
Observations	1337	1337	1580	1580
R^2	0.409	-	0.610	-
Bank FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes

NOTE: For each dependent variable, we compare the estimation results between OLS and 2SLS with instrument variable 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 levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

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

	Mg. Net Exp.			Loan Markups			Int. Ret. on Loans			Cost of Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FinTech Patents	-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)
Observations	760	760	760	760	760	760	760	760	760	757	757	757
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
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Time FE												

For each dependent variable, we run fixed-effect panel regression while adding bank-level controls and aggregate controls, respectively.

Table B.8: Effects of Patent-based Banking 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)
Observations	1562	1562	1562	1589	1589	1589
R^2	0.479	0.484	0.549	0.585	0.591	0.663
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Banks	-	Yes	Yes	-	Yes	Yes
Time FE	-	-	Yes	-	-	Yes

For each dependent variable, we run fixed-effect panel regression while adding bank-level controls and aggregate controls, respectively.

Table B.9: Effects of Banking Innovation on Loan Markup: using Growth

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

NOTE: We regress variable of interest on the growth of banking innovation to capture the time series information. Since we construct the measurement in spirit of intangible capital, the growth of intangible capital proxies for gross investment in innovation. The results still support our main conclusion that the growth of intangible capital significantly reduces marginal net expenses. We control for bank and year fixed effects with bank-level balance-sheet characteristics. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

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)
ΔInnovation$_{i,t-1}$	0.321**	0.022
	(0.162)	(0.141)
Observations	1401	1428
R^2	0.137	0.142
Bank FE	Yes	Yes
Bank Controls	Yes	Yes
Aggregate Controls	Yes	Yes
State Banks	Yes	Yes
Time FE	Yes	Yes

NOTE: We regress variable of interest on the growth of banking innovation to capture the time series information. Since we construct the measurement in spirit of intangible capital, the growth of the measurement proxies for gross investment in innovation. We control for bank and year fixed effects with bank-level balance-sheet characteristics. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

Table B.11: Effects of Banking Innovation on Loan Markup: Reconstruct Measurement

	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)
Observations	833	833	833	833
R^2	0.735	0.758	0.890	0.730
Bank FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Aggregate Controls		No		
Time FE	Yes	Yes	Yes	Yes

NOTE: We regress variable of interest on reconstructed measurement of banking innovation. We capitalized only 5% general administrative expenses as organizational capital. The results still support our main conclusion that the growth of intangible capital significantly reduces marginal net expenses. We control for bank and year fixed effects with bank-level balance-sheet characteristics. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

Table B.12: Effects of Banking Innovation on Risk-taking: Reconstruct Measurement

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

NOTE: We regress bank non-performing loan ratio and risk-weighted assets share on reconstructed measurement of banking innovation. We capitalized only 5% general administrative expenses as organizational capital. The results still support our main conclusion that the growth of intangible capital significantly reduces marginal net expenses. We control for bank and year fixed effects with bank-level balance-sheet characteristics. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

Table B.13: Effects of Banking Innovation on Bank Efficiency: Alternative Measures

	Cost/Income		Income/Asset		Profit/Asset	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
xxx	-1.606***	-15.588***	0.289***	0.954***	0.184***	1.340***
	(0.566)	(2.463)	(0.040)	(0.163)	(0.062)	(0.258)
Observations	1116	1145	1277	1307	1277	1307
R^2	0.748	0.638	0.824	0.785	0.528	0.396
Bank FE	Yes		Yes	Yes	Yes	Yes
Bank Controls	Yes		Yes	Yes	Yes	Yes
Aggregate Controls	Yes		Yes	Yes	Yes	Yes

NOTE: This table regress alternative measures of bank efficiency on banking innovation. Banking innovation significantly reduces a bank's cost-to-income ratio and increases profit and income. We control for bank and year fixed effects with bank-level balance-sheet characteristics. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

C Appendix for 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 identify 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 moments 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.

Table B.14: Heterogeneous Impacts of Banking Innovation on Cost-Reducing

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

NOTE: Intangible capital increases loan markups by significantly reducing non-interest net expenses. While this effect is significantly larger for banks with smaller NPL ratio, higher markup and larger size, therefore states banks. Bank control variables include leverage, size and revenue over assets. Aggregate time series control variables are the one-year deposit rate and GDP growth rate. We control for bank fixed effects. The numbers in the parentheses indicate robust standard errors. The levels of statistical significance are denoted by the asterisks: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The data sample ranges from 2008 to 2021 annually.

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

$$\begin{aligned}
\text{F.o.c for R\&D:} \quad \mu_0 &= \beta \frac{\partial z}{\partial i}(ml_0 + c_F)E_\chi \\
\text{F.o.c for } l_0^S\text{:} \quad \mu_0 + \phi_0 \xi &= \beta \left(1 + p^S(j)\frac{\epsilon - 1}{\epsilon}\right) E_\chi - \beta m(1-z)E_\chi \\
\text{F.o.c for } l_0^R\text{:} \quad \mu_0 + \phi_0 \xi \Psi &= \beta \left(1 + p^R(j)\frac{\epsilon - 1}{\epsilon}\right) \chi - \beta m(1-z)E_\chi.
\end{aligned}$$

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

$$\begin{aligned}
\mu_0 &\equiv F_i, \\
\mu_0 + \phi_0 \xi &\equiv F_S, \\
\mu_0 + \phi_0 \xi \Psi &\equiv F_R.
\end{aligned}$$

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, $\phi_0 > 0$. In this case, first using budget constraint, CAR, we can have the following set of conditions that should be satisfied with the optimal solution:

$$\begin{aligned}
0 &= e_0 + b_0 - l_0 - i, \\
l_0 &= l_0^S + l_0^R, \\
e_0 - \xi\left(l_0^S + \Psi l_0^R\right) &= 0, \\
i &\geq 0, l_0^S \geq 0, l_0^R \geq 0.
\end{aligned}$$

These conditions require that the initial values for the bank's capital and deposit, e_0 and b_0, should satisfy the following equations:

$$\begin{aligned}
l_0 &= e_0 + b_0 - i, \\
(\Psi - 1)\,\xi l_0^R &= e_0 - \xi l_0, \\
l_0^S &= l_0 - l_0^R, \\
\frac{e_0}{\xi \Psi} &\leq l_0 \leq \frac{e_0}{\xi}, \\
i &\geq 0,
\end{aligned}$$

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

$$\begin{aligned} e_0 + b_0 - \frac{e_0}{\xi} &\leq i \leq e_0 + b_0 - \frac{e_0}{\xi\Psi}, \\ 1 - \frac{e_0}{\xi(e_0+b_0)} &\leq \frac{i}{e_0+b_0} \leq 1 - \frac{e_0}{\xi\Psi(e_0+b_0)}. \end{aligned}$$

Note that for a given i, (l_0^S, l_0^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_0^S, l_0^R) and the expected value. Lastly, we pick up the best solution for i (if any).

- Case 2: if CAR is not binding; $\phi_0 = 0, e_0 - \xi\left(l_0^S + \Psi l_0^R\right) \geq 0$:

$$\begin{aligned} l_0 &= e_0 + b_0 - i \\ l_0 &= l_0^S + l_0^R, \\ e_0 &\geq \xi\left(l_0^S + \Psi l_0^R\right), \\ i &\geq 0, \end{aligned}$$

and the Focs can be presented as:

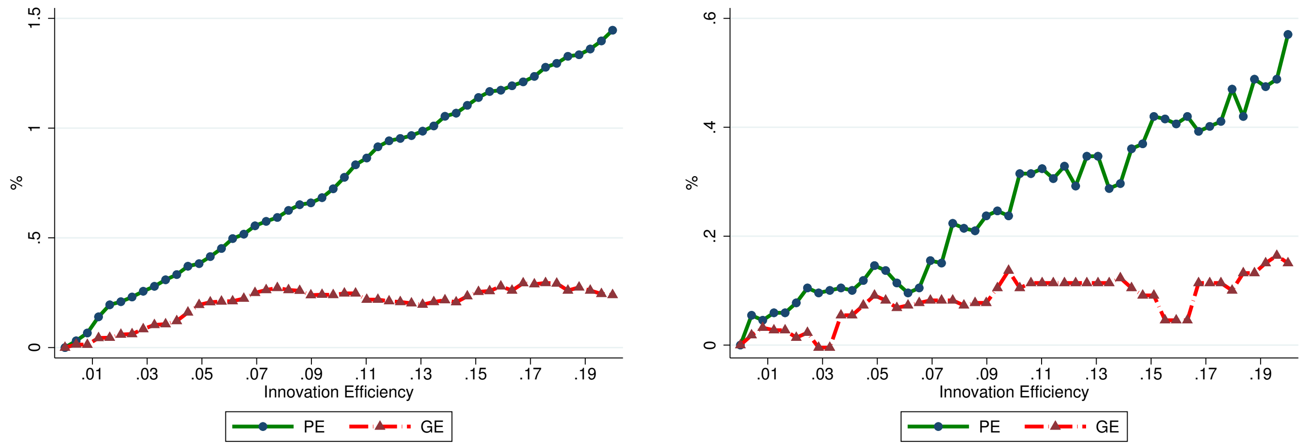
$$\begin{aligned} \mu_0 &\equiv F_i, \\ \mu_0 &\equiv F_S, \\ \mu_0 &\equiv F_R. \end{aligned}$$

For this case, we need to solve for i, l_0^S simultaneously, (l_0^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 with 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 $l_0^R : 0 \leq l_0^R \leq \frac{e_0 - \xi l_0}{(\Psi-1)\xi}$; then using Golden search method to find the best l_0^R so that the bank's expected value is maximized; if we find such a solution, then compute (l_0^S, l_0^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

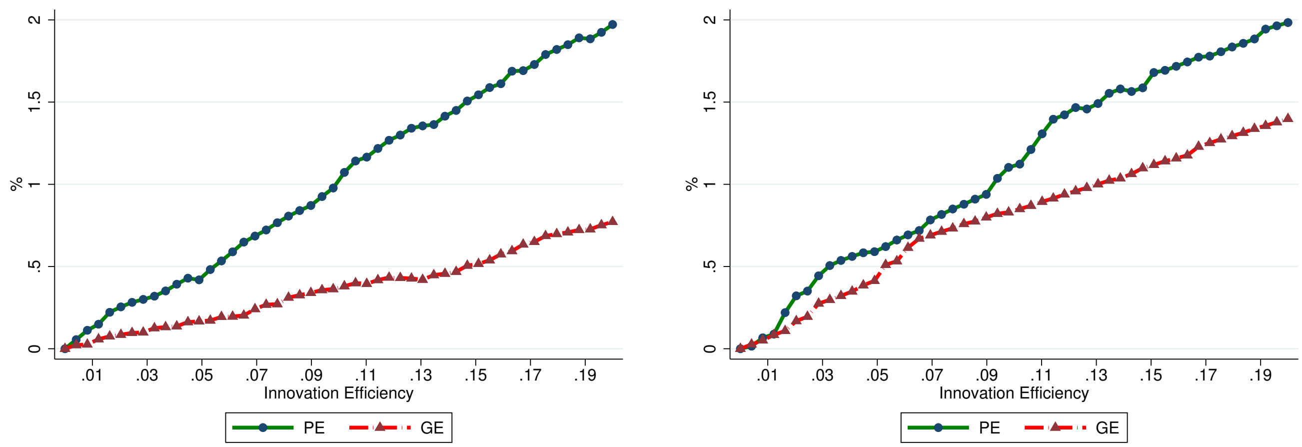
(a) Share for risky loans: Q1 (b) Share for risky loans: Q5



NOTE: These figures show the 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 the 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.