Financing Firm Innovation Through Bank Lending Channel: Evidence from China*

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Abstract

We study how monetary policy reallocates bank credit across loan contracts and how this reallocation affects innovation financing and bank fragility. Using a new firm–bank branch–loan type–quarter data set constructed from Chinese NEEQ-listed firms, we show that expansionary monetary shocks increase bank lending primarily by expanding unsecured credit. The response is stronger for non-state banks and is concentrated among firms with recent patenting activity. We develop a two-period general equilibrium model with heterogeneous banks. Firm innovation reduces pledgeable collateral, and banks choose between secured and unsecured lending subject to limited liability and a Value-at-Risk constraint. Monetary easing compresses unsecured-secured loan spreads, raises demand for unsecured borrowing, and induces a larger unsecured-loan response by non-state banks since they are relatively more risk-taking. Quantitatively, easing supports innovation financing by expanding unsecured credit, but it also raises default risk, especially among non-state banks. The results point to a loan composition channel of monetary policy and a macroprudential trade-off between financing innovation and preserving financial stability.

Keywords bank lending channel, loan type heterogeneity, unsecured credit, innovation

JEL Classification E44, E52, G21, G28

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1 Introduction

Innovation has become central to China's new stage of high-quality development: the Outline of the 15th Five-Year Plan (2026–2030) places high-quality, innovation-led growth at the center of the national development agenda. At the same time, China's financial system remains heavily bank dependent, especially for small and medium-sized enterprises. This institutional environment makes bank credit a key channel through which macroeconomic policy can support innovative activity. Yet patents, software, and other intangible assets are hard to pledge and costly for lenders to liquidate. As a result, innovation-intensive firms often need credit that is backed less by hard collateral. This observation raises a monetary-transmission question: when monetary policy eases, does bank credit simply expand, or does it also shift towards the unsecured contracts that are especially relevant for financing innovation?

We study this question using a new loan-level data set from firms listed on the National Equities Exchange and Quotations (NEEQ). Often viewed as China's counterpart to NASDAQ, the NEEQ is designed as an alternative investment market that promotes innovation and entrepreneurship among small and medium-sized enterprises. This institutional focus makes NEEQ firms especially relevant for studying how bank credit finances innovation. NEEQ firms disclose unusually detailed borrowing information in their annual reports, including lender names, bank branches, loan amounts, contract dates, loan types, and collateral or guarantee arrangements. We manually collect these disclosures and construct a panel at the firm–bank branch–loan-type–quarter level from 2014Q1 to 2024Q4. The granularity of the data allows us to observe not only how much a firm borrows, but also which bank branch supplies the credit and whether the contract is collateral-based or unsecured. This structure is crucial for separating bank-side loan-composition responses from borrower demand.

The empirical evidence reveals a loan composition channel of monetary policy. Expansionary monetary shocks raise both loan amounts and new loan issuance, but the response is not uniform across contracts or banks. When we split loans into mortgage, pledge, guarantee, mixed secured, and unsecured credit loans, the strongest response is concentrated in unsecured credit loans. The response is also systematically stronger for non-state banks than for state-owned banks. These patterns hold when we compare different bank branches lending to the same firm in the same quarter, and they become sharper for firms with recent patenting activity. Monetary easing therefore does more than increase aggregate bank lending: it reallocates credit toward unsecured loans, especially through non-state banks and toward innovation-intensive borrowers.

To interpret these facts, we develop a two-period general equilibrium model with heterogeneous banks and multiple loan contracts. On the firm side, innovation reduces pledgeable assets and raises the desired share of unsecured borrowing. On the bank side, secured loans

are supplied competitively, whereas unsecured loans are differentiated and expose banks to tail-state repayment risk. Banks choose loan allocations under limited liability and a Value-at-Risk constraint. A policy-rate cut lowers market-funding costs, relaxes the shadow cost of risk-bearing capacity, and compresses the unsecured-secured loan spread. This spread compression raises firm demand for unsecured borrowing. The effect is stronger for non-state banks because they have thinner buffers and operate closer to the risk boundary, so easing produces a larger relaxation of their constrained unsecured-loan supply.

The model also clarifies the policy implication. Monetary easing supports innovation financing by expanding unsecured credit, but the same reallocation increases bank fragility, especially among non-state banks. Quantitatively, a 1 percentage point policy-rate cut raises unsecured lending more for non-state banks than for state-owned banks and increases the default probability of non-state banks by more. Counterfactual macroprudential exercises show that policy instruments affecting tail-risk tolerance or unsecured exposure can dampen fragility, but they also alter the composition of credit available to innovative firms. We further dicuss the potential implications on improvements in state-owned banks' ability to process soft information, captured by a reduction on marginal cost of unsecured lending. As state-owned banks become more efficient in supplying unsecured credit, they absorb more risky loans and the default probability of non-state banks declines; at the same time, non-state banks lose unsecured-loan assets and lending relationships. This second margin links the model to recent policy concerns about the consolidation and reorganization of small banks in China, aiming to head off systemic risk.

Related Literature This paper contributes to three strands of the literature. First, it relates to work on heterogeneous monetary transmission across loan contract types. Li et al. (2022a) show that loans backed by different collateral classes respond differently to policy shocks, while Ivashina et al. (2022) document that cash-flow loans are much more sensitive to bank-balance-sheet transmission than asset-based lending. Our paper extends this line of research in two directions. We study a richer set of contract types in China, with particular emphasis on unsecured credit loans, and we show that contract heterogeneity interacts systematically with firm innovation intensity. In that sense, our paper also connects to the literature on how firm balance-sheet composition and debt structure shape monetary transmission (Caglio et al., 2021, Chen, 2021, Crouzet, 2021, Lee and Paluszynski, 2022, Lian and Ma, 2021, Öztürk, 2023, Zhang and Zhou, 2026), but our focus is not on how monetary policy affects firms' investment directly. Instead, we ask how banks reallocate across contract types when lending to firms with different degrees of collateral scarcity.

Second, our analysis speaks to the growing literature on bank heterogeneity, credit allocation, and monetary transmission in China using unique loan-level information. Studies such as Cong et al. (2019), Li et al. (2022b), Huang et al. (2023), Gambacorta et al. (2023), and Gao et al. (2023) show that Chinese credit markets are shaped by policy distortions, ownership het-

erogeneity, and informational frictions. Luo et al. (2023) emphasize that quantity-based monetary policy can reallocate funds across bank types, and Li et al. (2025) show that prudential regulation and monetary policy jointly reshape bank risk-taking and credit allocation. Complementing this work, Chen et al. (2025) highlight a macroprudential trade-off between policy transmission and systemic risk. Our contribution is to bring loan-type choice and borrower innovation into this discussion. Using NEEQ firms, we show that the differential response of state and non-state banks is not merely about total lending; it is especially about the allocation between secured and unsecured credit, and that allocation is strongest precisely for firms whose borrowing needs are more likely to be backed by future cash flow rather than hard collateral. We differ from this part of literature by using a unique loan-level data set covering from 2015 to 2024 that allows us to connect the micro allocation of loan contracts to a broader question about the trade-off between innovation financing and financial stability.

Third, we contribute to the literature on the relationship between credit market frictions and firm innovation. Reviews such as Kerr and Nanda (2015) and He and Tian (2020) emphasize that innovative activity depends crucially on financing conditions and on institutional environments that shape risk-taking, creditor rights, and the supply of capital. Recent evidence also shows that monetary policy can have persistent effects on innovation investment (Schmöller et al., 2025, Zhu and Chen, 2025). Relative to this literature, our paper takes firms' innovation status as given and studies a different margin: conditional on a firm's innovation intensity, what type of credit do banks supply, and which banks are more willing to supply it? This focus allows us to investigate how financial markets respond to innovation-driven borrowing needs.

The rest of the paper is organized in the following manner. Section 2 explains the empirical specification and presents empirical evidence. Section 3 proposes a simple toy model to illustrate the mechanism behind firm's R&D and alternative debt allocation and its potential impact to bank lending channel. The last Section concludes.

2 Empirical Studies

This section first describes our loan-level data and some stylized facts in the data. Then we study how bank lending behavior respond different in the transmission of monetary policy and how those effects vary with borrower innovation conditions. Section 2.1 introduces the loan-level data and reports basic summary statistics. Section 2.2 presents the baseline evidence on the bank lending channel and its variation across loan contracts. Section 2.4 then shows how these patterns become sharper when we condition on firm-level innovation proxies.

2.1 Loan-Level Data

We construct a new loan-level dataset from the annual reports of firms listed on the National Equities Exchange and Quotations (NEEQ), an over-the-counter market designed mainly for small and medium-sized enterprises in China. NEEQ firms disclose detailed information on their borrowing activities, including lender names, bank branches, loan amounts, loan types, contract dates, and collateral or guarantee arrangements. Comparable borrower-level debt disclosures are generally not available for firms listed on the main boards of the Chinese stock market.[1] This disclosure environment allows us to construct a unique panel of firm–bank branch–loan type–quarter observations and to study how banks reallocate credit across loan types in response to monetary policy shocks.

The dataset is distinctive in two respects. First, it preserves the identity of the lending bank branch, which allows us to compare lending decisions across banks serving the same borrower. Second, it records the loan type, which allows us to distinguish secured lending from unsecured credit. To the best of our knowledge, this is the first dataset that combines NEEQ loan disclosures with branch-level lender identities and loan-type classifications at quarterly frequency.[2] The final sample contains about 200,000 unique firm-loan pairs from 2014Q1 to 2024Q4.

A central institutional feature of China's banking system is the division between state-owned banks and non-state banks, as discussed in Chen et al. (2018, 2025). The top 5 largest banks are state-owned banks, operate under direct control and protection of the central government.[3] The remaining commercial banks are classified as non-state banks, including joint-stock banks, city commercial banks, and rural commercial banks, and other non-state-controlled banks. Non-state banks are generally more market-oriented and more sensitive to funding conditions and profitability. This ownership distinction is important for our question because monetary easing may affect not only the quantity of credit but also the type of loan contracts banks are willing to supply.

Several institutional differences make this ownership distinction central to our analysis. State-owned banks have nationwide branch networks, and more stable access to household deposits. Non-state banks, by contrast, usually have a narrower geographic footprint and rely more heavily on market-based or wholesale funding. They also serve a borrower base that

[1] The main boards of the Chinese stock market do not require firms to disclose complete borrowing activities at the loan-contract level, so borrower-level debt profiles are not observable.

[2] Luo et al. (2023) also use loan information from NEEQ firms, but their analysis aggregates the information to the bank level to study monetary policy transmission across state-owned and non-state banks. Our dataset instead keeps the firm–bank branch–loan type–quarter structure, which is essential for identifying loan-composition responses within the same borrower and quarter.

[3] They are: the Industrial and Commercial Bank of China, the Bank of China, the Construction Bank of China, the Agricultural Bank of China, and the Bank of Communications

contains a larger share of private firms and small and medium-sized enterprises, whose credit risk is less protected by implicit guarantees (Zhang and An, 2023). As a result, non-state banks are more sensitive to funding conditions and profitability, and their lending decisions respond more strongly to changes in monetary policy. This asymmetry is important for our setting because monetary easing may affect not only the total quantity of credit, but also banks' willingness to shift lending toward riskier, less collateralized loan contracts.

We classify loans into five categories used in Chinese banking practice: mortgage loans, pledge loans, guarantee loans, mixed secured loans, and unsecured credit loans. Mortgage and pledge loans are backed by tangible assets or pledgeable claims and are therefore closest to collateral-based lending. Guarantee and mixed loans occupy an intermediate position because repayment is supported by third-party guarantees or hybrid collateral arrangements. Unsecured credit loans rely most heavily on borrower cash flow, soft information, and the bank's willingness to bear downside risk.[4] This classification maps naturally into our empirical and theoretical distinction between secured and unsecured lending.

Table 1 summarizes the composition of lending by contract type. Panel A reports both the value-weighted share of total lending volume and the equally weighted share of loan observations. Guaranteed loans account for the largest fraction of observations, while mortgage loans account for the largest fraction of loan volume. Credit loans and mixed secured loans are increasing steadily in both volume and number over time. Panel B shows the summary statistics of loan size. Pledge loans have the largest mean and the widest upper tail, since firms on this market typically pledge their stock shares as collateral, and the value of those shares can be quite large.

Table 2 then reports loan type composition by bank ownership. This table is useful for two reasons. First, it shows that both state-owned and non-state banks are active in every major contract category, so the later regressions are not driven by one bank group being absent from a particular segment. Second, it highlights meaningful compositional differences even before imposing fixed effects. Within non-state banks, guaranteed loans account for the largest share of lending value, whereas mortgage loans carry the largest share within state-owned banks. Credit loans also differ in scale and turnover across ownership groups: they are larger on average among NSB and exhibit relatively higher new-loan shares. Taken together, these facts suggest that ownership heterogeneity is likely to operate through how banks reallocate across contracts rather than through a simple one-to-one specialization in a single loan type.

[4] Li et al. (2022a) classify unsecured credit loans as earnings-based loans.

Table 1: Descriptive statistics by loan type

Panel A. Prevalence of different loan types

Loan Type	% of loan volume (value-weighted)				% of loan number (equally-weighted)			
	2014	2018	2022	Full sample	2014	2018	2022	Full sample
Mortgage	37.09	41.16	20.11	26.61	36.08	29.40	18.47	22.49
Pledge	7.29	11.96	9.19	10.80	8.06	7.99	5.35	5.36
Guarantee	37.75	20.45	21.40	26.33	33.59	29.68	29.35	32.60
Credit	12.30	12.47	25.68	12.43	15.36	16.99	27.91	19.80
Mixed Secured	5.57	13.96	23.62	23.83	6.91	15.95	18.92	19.75

Panel B. Loan size (RMB million)

	Mean	S.D.	Median	1st pct.	99th pct.
Mortgage	17.86	49.07	9.75	0.40	139.86
Pledge	28.58	195.46	8.00	0.10	396.00
Guarantee	11.86	43.52	5.00	0.30	102.00
Credit	10.55	73.45	4.00	0.07	100.00
Mixed Secured	17.96	47.43	9.00	0.50	156.00

Notes: Panel A reports each loan type's share in total loan amount and total number of loan observations in 2014, 2018, 2022, and the full sample. Panel B reports descriptive statistics of loan size by each type, expressed in RMB million, over the full sample period.

Table 2: Loan-type composition by bank ownership

Loan Type	Obs.	Value Share (%)	Avg. Size (mn)	New Loan Share (%)	Number of Unique Firms	Number of Unique Branches
Panel A. Non-state banks (NSB)						
Mortgage	8,880	23.78	18.94	16.82	2,264	3,781
Pledge	2,650	11.00	29.37	25.94	871	1,279
Guarantee	15,531	27.48	12.51	23.81	2,671	6,031
Credit	8,820	15.43	12.37	26.19	2,452	3,854
Mixed Secured	8,519	22.30	18.52	20.66	1,882	3,608
Panel B. State-owned banks (SOB)						
Mortgage	6,257	31.55	16.31	42.35	1,561	1,946
Pledge	1,142	9.44	26.75	54.12	433	462
Guarantee	6,263	19.80	10.23	56.16	1,755	2,391
Credit	5,961	14.45	7.85	56.79	1,874	2,262
Mixed Secured	4,726	24.76	16.95	46.93	1,259	1,642

Notes: This table reports descriptive statistics for non-state banks (NSB) and state-owned banks (SOB), respectively. "Value Share" is the loan-type share in total lending amount within a bank-ownership group. "Avg. Size" is the average loan amount in RMB million. "New Loan Share" equals the fraction of positive firm–branch–loan-type relationships that appear for the first time in the sample. "Number of Unique Firms" and "Number of Unique Branches" correspond to the number of unique borrowers and lenders, respectively.

2.2 Loan Heterogeneity and the Bank Lending Channel

In this subsection, we consider the implications of the existence of different loan types for the transmission of monetary policy shocks. To do so, we test the bank lending channel of monetary policy by incorporating loan types. In spirit of Ivashina et al. (2022), our core insight is that the bank lending channel operates differentially for separate loan types, and that differences in risk-taking behavior across loan types play an important role in driving this difference.

To see whether the credit supply substantially differs across loan types. Our identification is thus based on differences across banks within the same firm and loan type pair. Intuitively, we compare the same firm which has unsecured credit loans from two (or more) banks that are differentially exposed to changes in monetary policy. Our baseline specification is

$$Y_{fblt} = \beta_1 \epsilon_{t-1} + \beta_2 \epsilon_{t-1} \times \text{NSB}_b + \beta_3 Z_{t-1} + \beta_4 Z_{t-1} \times \text{NSB}_b + \eta_{flt} + e_{fblt}, \tag{1}$$

where f denotes the firm, b the bank branch, l the loan type, and t the quarter. The dependent variable Y_{fblt} is either the log loan amount, which captures the intensive margin, or a new-loan indicator, which captures the extensive margin. The new-loan indicator equals one when a firm–branch–loan-type combination appears for the first time in the sample. ϵ_{t-1} is an expansionary monetary-policy shock constructed as the negative of the quarterly change in R007, a market-determined interbank rate that closely tracks policy conditions and is widely used in the literature on monetary transmission in China (Li et al., 2022a, Luo et al., 2023). A larger ϵ_{t-1} therefore corresponds to monetary easing. We also verify that the results are robust to using an alternative expansionary shock constructed from the negative of the Taylor-rule residuals following Chen et al. (2025). NSB_b is an indicator for whether the bank is non-state.[5] The interaction between the policy shock and the non-state-bank indicator captures whether non-state banks respond more strongly than state-owned banks to expansionary policy. Z_{t-1} denotes macro controls including lagged GDP growth and inflation rate. η_{flt} corresponds to firm $\times$ loan type $\times$ quarter fixed effects, which absorbs borrower-side demand at the firm–loan-type–quarter level, so identification comes from comparing how different banks lend to the same firm in the same quarter. Standard errors are clustered at the bank branch level.

Table 3 reports the baseline estimates. Columns (1) through (4) control for firm-quarter fixed effects and therefore compare lending outcomes across bank branches serving the same firm in the same quarter. Columns (5) through (8) further control for firm-loan type-quarter fixed effects to absorb not only borrower-level credit demand at the quarterly frequency, but also any short-run shift in the firm's demand across different contract types. Relative to the specifications with firm-quarter fixed effects only, the explanatory power of differential impacts rises

[5] Because branch-level balance-sheet variables are not available for the full sample, we proxy intermediary heterogeneity with bank ownership, distinguishing non-state banks from state-owned banks.

Table 3: Baseline bank lending channel estimates

	Firm-quarter FE				Firm-loan type-quarter FE			
	Loan Amount		New Loan		Loan Amount		New Loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ϵ_{t-1}	0.793***		0.052***		0.729***		0.048***	
	(0.058)		(0.004)		(0.059)		(0.004)	
ΔGDP_{t-1}	-0.046***		-0.003***		-0.046***		-0.003***	
	(0.006)		(0.000)		(0.006)		(0.000)	
$\epsilon_{t-1} \times I(\text{NSB}_b)$		0.608***		0.037***		0.681***		0.041***
		(0.190)		(0.012)		(0.216)		(0.013)
$\Delta GDP_{t-1} \times I(\text{NSB}_b)$		-0.030*		-0.002*		-0.032*		-0.002*
		(0.016)		(0.001)		(0.019)		(0.001)
Observations	154,354	116,918	154,354	116,918	153,819	92,092	153,819	92,092
R^2	0.077	0.566	0.076	0.571	0.112	0.594	0.112	0.598
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	-	Yes	-	-	-	-	-
Firm-loan type FE	-	-	-	-	Yes	-	Yes	-
Firm-quarter FE	-	Yes	-	Yes	-	-	-	-
Firm-loan type-quarter FE	-	-	-	-	-	Yes	-	Yes

Notes: The unit of observation is a firm–bank branch–loan-type–quarter. The dependent variable is either log loan amount or a new-loan indicator. ϵ_{t-1} is the lagged expansionary shock defined as the negative of the quarterly change in R007, so larger values correspond to monetary easing. Columns (1)–(4) include firm or firm-quarter fixed effects; columns (5)–(8) include firm–loan-type or firm–loan-type–quarter fixed effects. All columns include macro controls. Standard errors clustered at bank branch level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

once loan-type-specific demand is absorbed, while the magnitude of the coefficients remains broadly stable. This pattern suggests that the baseline ownership differential is not driven by changes in firms' desired loan mix. Instead, the estimates point to bank-side contract allocation as the key source of variation. In that sense, the coefficients in columns (1) through (4) can be interpreted as weighted averages of the loan-type-specific responses, with the weights determined by the number of observations in each contract category.

Specifically, according to the estimates in column (1) of Table 3, a one standard deviation (SD) cut in interest rates results in an increase in log of loan amount by 0.266 (= 0.793 $\times$ 0.335), corresponding to roughly a 30% increase in loan size.[6] The interaction term in column (2) is positive and statistically significant, indicating that non-state banks expand lending more aggressively than state-owned banks in response to monetary easing. Column (2) indicates that a one SD reduction in interest rates for non-state banks results in an additional increase in loan amount by approximately 22.6% (= 0.608 $\times$ 0.335 in log amount). The estimates in columns (3) and (4) show a similar pattern for the extensive margin: the new loan issuance increases significantly on average, and the increase is stronger for non-state banks. These results are consistent with the existence of a bank lending channel in which monetary policy affects credit supply, and they also suggest that the channel operates more strongly through non-state banks than through state-owned banks.

Table 4 further drills down to the loan-type dimension and asks which contracts drive the baseline ownership differential. This decomposition is important because the same total lending response could in principle arise from very different reallocations across different loan types. If the bank lending channel in this setting operates through risk-taking incentives, the strongest ownership heterogeneity should appear precisely in the contract type with the weakest collateral protection.

In this table, all specifications include firm-quarter fixed effects with standard errors clustered at bank branch level. Therefore, the variation is entirely cross-bank within the same borrower and quarter. Panel A reports the average response to an interest rate cut, while Panel B reports the differential response using interactions with the non-state-bank indicator. The first five columns use loan amount as the dependent variable, while the last five columns use the new loan indicator. The results show that the average easing effect is visible for all loan categories, but the ownership interaction is not evenly distributed across them. In particular, the non-state-bank interaction is economically and statistically strongest for unsecured credit loans: the coefficient is positive for both loan amount and new loan issuance, while the corresponding ownership interactions for mortgage, pledge, guarantee, and mixed loans are much smaller and generally insignificant. The evidence therefore suggests that the ownership differential in Table 3 is mainly a credit-loan phenomenon rather than a broad-based difference

[6]The descriptive statistics of the main regression variables can be found in Appendix Table A.1.

across all loan types.

Table 4: Loan-type heterogeneity in the bank lending channel

Dependent Variable:	Loan Amount					New Loan				
Panel A:	Mortgage (1)	Pledge (2)	Guaranteed (3)	Credit (4)	Mixed (5)	Mortgage (6)	Pledge (7)	Guaranteed (8)	Credit (9)	Mixed (10)
ϵ_{t-1}	0.698***	0.719*	0.452***	1.507***	0.524**	0.045***	0.043*	0.030***	0.100***	0.034***
	(0.158)	(0.394)	(0.148)	(0.203)	(0.209)	(0.010)	(0.024)	(0.009)	(0.013)	(0.013)
ΔGDP_{t-1}	-0.065***	-0.041	-0.038***	-0.060***	-0.019	-0.004***	-0.003	-0.002***	-0.004***	-0.001
	(0.014)	(0.028)	(0.013)	(0.016)	(0.016)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	23,661	4,699	30,639	17,407	18,593	23,661	4,699	30,639	17,407	18,593
R^2	0.138	0.155	0.088	0.130	0.119	0.140	0.159	0.087	0.128	0.119
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable:	Loan Amount					New Loan				
Panel B:	Mortgage (1)	Pledge (2)	Guaranteed (3)	Credit (4)	Mixed (5)	Mortgage (6)	Pledge (7)	Guaranteed (8)	Credit (9)	Mixed (10)
$\epsilon_{t-1} \times I(\text{NSB}_b)$	0.234	0.873	-0.529	2.108***	-0.302	0.026	0.067	-0.027	0.135***	-0.025
	(0.580)	(1.947)	(0.624)	(0.812)	(0.760)	(0.035)	(0.115)	(0.039)	(0.052)	(0.047)
$\Delta GDP_{t-1} \times I(\text{NSB}_b)$	-0.050	-0.395***	-0.031	-0.033	0.052	-0.003	-0.024***	-0.002	-0.002	0.003
	(0.050)	(0.109)	(0.048)	(0.063)	(0.047)	(0.003)	(0.007)	(0.003)	(0.004)	(0.003)
Observations	10,893	1,862	19,537	8,465	10,789	10,893	1,862	19,537	8,465	10,789
R^2	0.653	0.617	0.574	0.629	0.607	0.660	0.626	0.577	0.634	0.611
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table estimates the baseline specification separately by loan type. Columns (1)–(5) use log loan amount; columns (6)–(10) use the new-loan indicator. Panel A reports the average response to the expansionary shock ϵ_{t-1}. Panel B reports the interaction between ϵ_{t-1} and the non-state-bank indicator. All columns include macro controls. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This pattern is economically meaningful because credit loans are the contract type that depends least on hard collateral and most on the lender's willingness to bear cash-flow risk. Mortgage and pledge loans also respond to monetary policy, but the ownership split is much weaker there. The heterogeneity is concentrated exactly where risk-taking considerations should matter most since unsecured credit loans are in nature riskier than other secured loans. Therefore, when interest rates are lower, smaller banks will increase risk, which is equivalent to making more credit loans. This is consistent with the idea that the underlying mechanism driving our results being related to the type of the underlying collateral and associated default risk of the different loan types. In addition, it is also consistent with the facts that non-state banks are more responsive to monetary policy because they have stronger incentives to take risk, and that the risk-taking channel operates most strongly through the contract type that depends most on lender discretion and least on collateral.

2.3 Innovation Heterogeneity

The baseline results establish that the ownership differential in monetary transmission is concentrated in unsecured credit loans. A natural question is whether this differential becomes

stronger for innovative-intensive firms whose financing needs are more likely to be connected with credit loans due to their larger share of R&D investment. We study this issue by augmenting the baseline specifications with a further triple interaction between the policy shock, bank ownership, and a lagged firm-level patent-application dummy ($\epsilon_{t-1} \times \text{NSB}_b \times \text{Patent}_{f,t-1}$). The purpose of this exercise is not to claim that NEEQ firms split neatly into innovative and non-innovative groups; if anything, the NEEQ already contains a relatively innovation-intensive set of borrowers. Instead, the lagged patent indicator helps identify sharper within-sample variation in firms' recent innovation activity and asks whether banks allocate credit loans differently when such signals are present.

This specification is useful because it keeps the empirical focus on bank-side loan type allocation. By conditioning on firm-quarter fixed effects, we compare how different banks lend to the same firm in the same quarter. The coefficient on the baseline interaction, $\epsilon_{t-1} \times \text{NSB}_b$, captures whether non-state banks react differently from state-owned banks on average. The coefficient on the triple interaction, $\epsilon_{t-1} \times \text{NSB}_b \times \text{Patent}_{f,t-1}$, then asks whether this ownership differential itself varies with an observable innovation signal. In other words, the triple interaction does not measure whether innovative firms borrow more in general; it measures whether, for the same firm and quarter, the cross-bank reallocation induced by monetary policy is more pronounced when the borrower has recently displayed innovative activity.

Table 5: Innovation heterogeneity in loan-type responses

Dependent Variable:	Loan Amount					New Loan				
	Mortgage (1)	Pledge (2)	Guaranteed (3)	Credit (4)	Mixed (5)	Mortgage (6)	Pledge (7)	Guaranteed (8)	Credit (9)	Mixed (10)
$\epsilon_{t-1} \times I(\text{NSB}_b) \times \text{Patent}_{f,t-1}$	0.853	-3.677	0.043	5.429***	0.386	0.035	-0.210	0.020	0.301***	0.031
	(1.302)	(3.372)	(1.213)	(1.684)	(1.551)	(0.079)	(0.201)	(0.075)	(0.107)	(0.095)
Observations	10,893	1,862	19,537	8,465	10,789	10,893	1,862	19,537	8,465	10,789
R^2	0.654	0.619	0.574	0.629	0.607	0.660	0.628	0.577	0.634	0.611
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table adds heterogeneity by firm innovation. $\text{Patent}_{f,t-1}$ equals one if the firm filed a patent application in the previous period. Columns (1)–(5) use log loan amount; columns (6)–(10) use the new-loan indicator. The coefficient of interest is the triple interaction between ϵ_{t-1}, the non-state-bank indicator $I(\text{NSB}_b)$, and the patent dummy $\text{Patent}_{f,t-1}$. All columns include firm-quarter fixed effects, lower-order interactions, and macro controls. Standard errors clustered at bank branch level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 shows that the additional heterogeneity is concentrated precisely where the risk-taking interpretation would predict it to be. The triple interaction is economically large and statistically significant for credit loans in both the loan amount and new loan issuance, while it is small and imprecisely estimated for other loan types. Because the policy shock is defined so that a larger value corresponds to monetary easing, these estimates imply that, conditional on recent patenting activity, non-state banks expand unsecured credit more aggressively than state-owned banks when policy loosens. Put differently, recent innovation signals amplify the

ownership differential, but mainly in the loan category that depends least on collateral and most on lender willingness to bear risk.

This pattern strengthens the interpretation of the earlier reduced-form evidence. The key result is not simply that innovative firms borrow more, nor that non-state banks lend more in the aggregate. Rather, when firms display recent innovation activity, the cross-bank composition of lending shifts further toward unsecured credit in easing episodes, and that shift is disproportionately driven by non-state banks. This is consistent with the idea that innovation-intensive firms are harder to finance through hard-asset-based contracts and therefore benefit more from banks willing to extend cash-flow-based credit.

At the same time, the estimates should be interpreted carefully. Our design is centered on bank lending behavior, not on the causal effect of debt structure on subsequent innovation outcomes. We therefore treat firm-level innovative activity as an observable borrower characteristic that changes the desirability of different contract types from the bank's perspective. Under this interpretation, Table 5 provides an important bridge to the model developed in the next section: when monetary easing raises incentives to take risk, non-state banks respond by expanding the form of lending that is most useful for innovation-oriented firms, namely unsecured credit loans. This also points to the broader trade-off explored later in the paper: the same mechanism that relaxes financing constraints for innovative firms may simultaneously raise risk on bank balance sheets.

2.4 Robustness Checks

We conduct two sets of robustness checks. First, following Chen et al. (2025), we replace the baseline expansionary R007 shock with an alternative expansionary shock constructed as the negative of Taylor-rule residuals. Tables A.2–A.4 show that the main patterns are qualitatively unchanged under this alternative measure: monetary easing still raises lending on average, non-state banks still expand more strongly, and the ownership differential remains concentrated in unsecured credit loans.

Second, Appendix Table A.5 provides an additional robustness check from branch-level extensive margin. There, we aggregate the data to the firm–branch–quarter level, construct the share of credit loans in each branch's lending to a firm, and regress that share on the expansionary shock interacted with the non-state-bank indicator. The interaction term is positive under both the baseline R007-based shock and the alternative Taylor-residual shock, confirming that monetary easing raises the credit-loan share more strongly for non-state banks than for state-owned banks.

3 Model

Motivated by the empirical evidence, this section develops a two-period structural general equilibrium model with heterogeneous banks. Time is indexed by $t \in \{0, 1\}$. The economy consists of a representative household, a representative firm, and a continuum of banks with unit measure.

Banks raise deposits and market funding in period 0 and lend to the firm through secured and unsecured contracts. Secured loans are backed by pledgeable assets, whereas unsecured loans are repaid only when the firm succeeds. The model has two central ingredients. First, innovation reduces pledgeable collateral and shifts firm borrowing toward unsecured credit. Second, banks choose loan allocations under limited liability, VaR discipline, and ownership-specific funding conditions. These frictions generate a risk-taking channel of monetary policy: easing lowers banks' funding costs, compresses the relative price of unsecured credit, and induces a stronger unsecured-loan response among non-state banks. The same mechanism that supports innovative firms therefore also raises bank fragility.

We describe the household, firm, and bank blocks in turn.

3.1 Households

A representative household is risk neutral and has preferences

$$C_0 + \beta C_1, \qquad \beta \in (0, 1). \tag{2}$$

The household owns all firms and banks, supplies deposits to banks in period 0, and receives profits and transfers in period 1. To allow ownership-specific funding costs, the household allocates savings across two deposit instruments, D_{SOB} and D_{NSB}, issued by state-owned and non-state banks. Following Chen et al. (2025), we assume that deposits at non-state banks carry an additional liquidity cost. If this cost is linear with slope $\tau_D > 0$, the household Euler equations are

$$\beta(1 + r^D_{SOB}) = 1, \tag{3}$$

$$\beta(1 + r^D_{NSB}) = 1 + \tau_D, \tag{4}$$

which implies

$$r^D_{NSB} > r^D_{SOB}. \tag{5}$$

When a bank fails, deposit insurance repays depositors and is financed by lump-sum transfers from the household sector. This assumption keeps depositors fully insured while leaving bank

shareholders exposed to limited liability.

3.2 Firms

The representative firm undertakes total investment K in period 0. A fraction $\psi \in [0,1]$ of this investment is R&D or other intangible expenditure, while the remaining fraction $1-\psi$ is tangible and pledgeable. We treat ψ as exogenous, consistent with the empirical design in which recent patent applications proxy for a firm's innovation activity. The firm finances investment with secured and unsecured composite loans:

$$K = L^s + L^u. \tag{6}$$

Secured loan amount depends on the level of tangible capital investment that can be pledged as collateral ($L^s = \theta(1-\psi)K$, where $\theta \in (0,1)$). In period 1, the project succeeds with probability $\chi \in (0,1)$ and earns gross revenue $\big[1+A(\psi)\big]g(K)$, where $g'(K) > 0$, $g''(K) < 0$, and $A(\psi)$ captures project total factor productivity. With probability $1-\chi$, the project fails, the firm produces only $g(K)$, and unsecured debt is not repaid. The two state payoffs are

$$\pi^H = \big[1+A(\psi)\big]g(K) - (1+r_t^s)L^s - (1+r_t^u)L^u, \tag{7}$$

$$\pi^L = g(K) - (1+r_t^s)L^s. \tag{8}$$

Using (6) together with the collateral borrowing amount, the firm's optimality condition can be written as

$$\big[1+\chi A(\psi)\big]g'(K) = \theta(1-\psi)(1+r_t^s) + \chi\big[1-\theta(1-\psi)\big](1+r_t^u). \tag{9}$$

This firm block implies a simple composition force. A higher innovative investment share reduces pledgeable collateral and lowers the amount of secured borrowing. The residual financing need must be met with unsecured credit, so a higher ψ shifts loan demand toward unsecured loans.

Since the unsecured loan market is monopolistic competitive, we introduce a loan-packing intermediary that aggregates bank loans before lending to the firm. The intermediary combines loans supplied by state-owned and non-state banks through a CES aggregator:

$$L^u = \left[\omega_{SOB}^{1/\sigma}\left(L_{SOB}^u\right)^{\frac{\sigma-1}{\sigma}} + \omega_{NSB}^{1/\sigma}\left(L_{NSB}^u\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

with aggregate price index

$$r_t^u = \left[\omega_{SOB}\left(r_{SOB,t}^u\right)^{1-\sigma} + \omega_{NSB}\left(r_{NSB,t}^u\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}.$$

The corresponding type-level loan demands are

$$L_{SOB}^u = \omega_{SOB}\left(\frac{r_{SOB,t}^u}{r_t^u}\right)^{-\sigma} L^u, \qquad L_{NSB}^u = \omega_{NSB}\left(\frac{r_{NSB,t}^u}{r_t^u}\right)^{-\sigma} L^u.$$

Within each ownership type, unsecured loans are differentiated across retail banks. The within-type CES aggregator is

$$L_\tau^u = \left[\int_i \ell_\tau^u(i)^{\frac{\varepsilon-1}{\varepsilon}} di\right]^{\frac{\varepsilon}{\varepsilon-1}},$$

with price index

$$r_{\tau t}^u = \left[\int_i (r_{it}^u)^{1-\varepsilon} di\right]^{\frac{1}{1-\varepsilon}},$$

which implies individual unsecured-loan demand

$$\ell_{it}^u = \left(\frac{r_{it}^u}{r_{\tau t}^u}\right)^{-\varepsilon} L_{\tau t}^u. \tag{10}$$

combining with the sectoral CES demand, we can have:

$$\ell_{it}^u = \left(\frac{r_{it}^u}{r_{\tau t}^u}\right)^{-\varepsilon} \omega_\tau \left(\frac{r_{\tau t}^u}{r_t^u}\right)^{-\sigma} L_t^u$$

3.3 Banks

The banking sector consists of a continuum of two-period banks indexed by $i \in I$. Banks differ by ownership type $\tau(i) \in \{SOB, NSB\}$, where SOB denotes state-owned banks and NSB denotes non-state banks. Banks finance lending activities through equity, deposits, and wholesale market funding. Banks are risk neutral agents who maximize expected second period prot subject to a Value-at-Risk (VaR) constraint. They also benet from limited liability.

The balance sheet of bank i at the end of period t is given by:

$$\ell_{it}^u + \ell_{it}^s = e_{it} + b_{it} + G_{it}, \tag{11}$$

where ℓ_{it}^u and ℓ_{it}^s denote the unsecured and secured loan assets held by bank i, respectively. b_{it} the deposit amount contracted at interest rate $r_{\tau t}^D$, and e_{it} the initial equity. For simplicity, we assume e_{it} and b_{it} are randomly drawn from a joint distribution. G_{it} denote the market

funding, following Wang et al. (2022), the policy rate f_t is the marginal cost of this market funding. Thus monetary policy affects the bank directly through its liability side rather than through an exogenous shift in loan demand.

At the beginning of period t, bank i banks allocate available funding across secured and unsecured lending. Equity e_{it} and deposits b_{it} are predetermined and heterogeneously distributed across banks. Market funding G_{it} is elastically supplied at marginal cost f_t, which coincides with the policy rate. Monetary policy therefore affects banks directly through the liability side of their balance sheets.

Secured loans are collateralized by pledgeable assets and are supplied in a competitive market. Banks therefore take the secured lending rate r_t^s as given. Unsecured loans are differentiated across banks according to the CES demand system described in (10). As a result, banks possess monopolistic power in unsecured lending and optimally choose the unsecured lending rate r_{it}^u.

On the liability side, banks raise deposits at ownership-specific funding costs $r_{\tau t}^D$, where $r_{NSB,t}^D > r_{SOB,t}^D$. Let $c_{\tau,s}$ and $c_{\tau,u}$ denote the marginal operating costs associated with secured and unsecured lending, respectively, and let c_F denote a fixed operating cost.

The loan project outcomes are realized in the second period, with probability χ, the economy enters a good state H, in which all loans are fully repaid. With probability $1-\chi$, the economy enters a bad state L. Secured loans are fully recoverable in both states because they are backed by pledgeable collateral. Unsecured loans, however, are subject to repayment risk. In the bad state, the recovery value of unsecured lending is

$$\omega_{it}\ell_{it}^u,$$

where ω_{it} is the idiosyncratic recovery shock drawn from the distribution $F_\tau(\omega)$.

Limited liability implies that shareholders receive

$$\max\{\pi_{it}, 0\},$$

and therefore do not internalize losses beyond bank equity.

The resulting state-contingent profits are:

$$\pi_{it}^H = r_t^s\ell_{it}^s + r_{it}^u\ell_{it}^u - c_{\tau,s}\ell_{it}^s - c_{\tau,u}\ell_{it}^u - c_F - r_{\tau t}^D b_{it} - f_t G_{it}, \tag{12}$$

$$\pi_{it}^L = r_t^s\ell_{it}^s + \omega_{it}\ell_{it}^u - c_{\tau,s}\ell_{it}^s - c_{\tau,u}\ell_{it}^u - c_F - r_{\tau t}^D b_{it} - f_t G_{it}. \tag{13}$$

The difference between (12) and (13) highlights the risk-taking margin: unsecured lending earns a higher payoff in the good state but exposes the bank to larger losses in the bad state.

Following Coimbra and Rey (2017), we introduce a regulatory VaR constraint which limits

bank exposure to tail losses. Specifically, the probability that bad-state losses exceed the bank's equity buffer must remain below a regulatory threshold $\bar{\alpha}$:

$$\Pr\Big(\pi_{it}^{L} + e_{it} < 0\Big) \leq \bar{\alpha}, \tag{14}$$

where $\bar{\alpha}$ is the common regulatory tolerance for VaR violations. Equity relaxes the constraint by increasing the buffer available in the bad state, whereas unsecured lending tightens it because a larger ℓ_{it}^{u} raises exposure to the tail recovery shock.

3.4 Bank's Problem and Equilibrium Condition

At the beginning of period t, after observing the policy rate f_t and taking as given the deposit rate $r_{\tau t}^{D}$ and the competitive secured-loan rate r_t^{s}, bank i chooses unsecured loan rate r_{it}^{u}, unsecured lending ℓ_{it}^{u}, secured lending ℓ_{it}^{s}, and market funding G_{it}. Since the good state is solvent by construction, limited liability matters only in the bad state. Let $\mathbb{I}_{it}$ denote the bad-state survival indicator, with $\mathbb{I}_{it} = 1$ if the bank survives and $\mathbb{I}_{it} = 0$ otherwise. The bank solves

$$V_{it} = \mathbb{E}_0 \max_{\{r_{it}^{u}, \ell_{it}^{u}, \ell_{it}^{s}, G_{it}\}} \{\pi_{it}, 0\}, \tag{15}$$

subject to the balance-sheet identity (11), the individual unsecured-loan demand curve (10), nonnegativity of loans, and the VaR constraint (14).

We define equilibrium in this economy as follows.

An equilibrium consists of firm investment K_t, aggregate secured and unsecured lending (L_t^{s}, L_t^{u}), loan rates $(r_t^{s}, r_t^{u}, \{r_{it}^{u}\}_{i\in I})$, bank allocations $\{\ell_{it}^{s}, \ell_{it}^{u}, G_{it}\}_{i\in I}$, VaR multipliers $\{\mu_{it}\}_{i\in I}$, and survival indicators $\{\mathbb{I}_{it}\}_{i\in I}$ such that:

(i) each bank solves the optimization problem given by (15);

(ii) the representative firm chooses investment and loan composition subject to its financing constraints;

(iii) the representative household maximizes utility and supplies deposits to banks;

(iv) secured and unsecured loan markets clear:

$$L_t^{s} = \int_I \ell_{it}^{s}\, di, \qquad L_t^{u} = \left[\sum_{\tau\in\{SOB,NSB\}} \omega_{\tau}^{1/\sigma} \left(L_{\tau t}^{u}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

with $L_{\tau t}^{u}$ generated by the within-type CES aggregator.

(v) Let total initial bank assets be

$$\bar{A}_t = \int_I [e_{it} + b_{it}]\, di.$$

In the numerical exercises, aggregate quantities can be scaled by $\bar{A}_t$.

3.5 Loan Composition Channel in the Monetary Policy Transmission

This subsection links monetary policy to loan composition through the unsecured-secured spread. A lower policy rate reduces the cost of liability-side market funding. It also improves bad-state solvency and relaxes the VaR constraint, thereby lowering the shadow cost of supplying unsecured credit. Because unsecured loans carry tail-state repayment risk while secured loans do not, the decline in this shadow cost enters unsecured pricing more strongly than secured pricing. The spread compression raises firm demand for unsecured borrowing and reallocates credit toward banks whose risk-bearing capacity is most sensitive to monetary easing. This effect is larger for non-state banks because they have thinner equity buffers, higher deposit costs, and greater reliance on market funding. The following proposition summarizes the pricing and allocation effects.

Proposition 1. A cut in the policy rate f_t:

(i) compresses the unsecured-secured spread;

(ii) raises firm demand for unsecured loans; and

(iii) raises unsecured loan supply more strongly for non-state banks.

Proof. Let λ_{it} denote the multiplier on the balance-sheet constraint (11) and let μ_{it} denote the multiplier on the VaR constraint (14). Define $S_{it} \equiv \chi + (1-\chi)\mathbb{I}_{it}$. Appendix B solves the bank's optimization problem in detail.

Following a policy-rate cut, the change in the unsecured-secured spread is given by:

$$\frac{\partial}{\partial f_t}(r^u_{it} - r^s_t) = \underbrace{\frac{\varepsilon}{\varepsilon - 1}\frac{S_{it} + \mu_{it}}{\chi} - 1}_{\text{direct funding-cost effect}} + \underbrace{\frac{\varepsilon}{\varepsilon - 1}\frac{f_t + c_{\tau,u} - \omega_{\alpha,\tau}}{\chi}\frac{\partial \mu_{it}}{\partial f_t}}_{\text{VaR shadow-cost effect}}. \tag{16}$$

The first term captures direct pass-through from market funding costs into unsecured pricing relative to competitive secured pricing. The second term captures the endogenous response of the VaR shadow value. A lower policy rate improves bad-state solvency by reducing the cost of market funding. Hence the VaR constraint becomes less costly to satisfy and μ_{it} falls when f_t falls, or equivalently $\partial \mu_{it}/\partial f_t > 0$ around the binding region. Under the calibrated parameter region in which unsecured exposure is risky in the lower tail, (16) is positive. Therefore a policy-rate cut compresses $r^u_{it} - r^s_t$.

For part (ii), the firm optimality condition implies

$$\frac{dK_t}{df_t} = \frac{\theta(1-\psi_t)\, dr_t^s/df_t + \chi[1-\theta(1-\psi_t)]\, dr_t^u/df_t}{[1+\chi A(\psi_t)]\, g''(K_t)} < 0,$$

because $g''(K_t) < 0$ and loan rates rise with the policy rate. Thus a policy-rate cut raises equilibrium investment K_t. Since unsecured demand is

$$L_t^u = [1-\theta(1-\psi_t)]K_t,$$

the cut also raises firm demand for unsecured loans.

For part (iii), the individual demand curve gives

$$\frac{\partial \log \ell_{it}^u}{\partial f_t} = -\varepsilon \frac{\partial \log r_{it}^u}{\partial f_t} + \frac{\partial \log L_{\tau t}^u}{\partial f_t}.$$

Since $\partial r_{it}^u/\partial f_t > 0$, a policy-rate cut raises individual unsecured lending. The response is stronger for banks whose VaR multiplier is more sensitive to the policy rate. Non-state banks have smaller equity buffers and higher funding costs, so they operate closer to the VaR boundary. Formally, in the binding region,

$$\frac{\partial \mu_{it}^{NSB}}{\partial f_t} > \frac{\partial \mu_{it}^{SOB}}{\partial f_t} \geq 0.$$

Therefore a reduction in f_t lowers the unsecured rate quoted by non-state banks by more, shifting a larger share of unsecured lending toward them under the CES demand system.

The innovation interaction follows from the same pricing equation. Differentiating the unsecured-pricing equation in Appendix (B.7) with respect to f_t and ψ_t gives

$$\frac{\partial^2 r_{it}^u}{\partial f_t\, \partial \psi_t} = \frac{\varepsilon}{\varepsilon - 1}\frac{1}{\chi}\left[\frac{\partial \mu_{it}}{\partial \psi_t} + (f_t + c_{\tau,u} - \omega_{\alpha,\tau})\frac{\partial^2 \mu_{it}}{\partial f_t\, \partial \psi_t}\right]. \tag{17}$$

A higher ψ_t reduces pledgeable collateral and increases the required unsecured share L_t^u/K_t. This tightens the VaR constraint for banks with thin buffers, implying $\partial \mu_{it}/\partial \psi_t > 0$. Moreover, when ψ_t is high, a given policy-rate cut produces a larger relaxation of tail-state funding pressure, so $\partial^2 \mu_{it}/\partial f_t \partial \psi_t > 0$ in the binding region. Equation (17) is therefore positive for constrained non-state banks. Since the demand elasticity maps lower unsecured rates into higher quantities, monetary easing raises non-state-bank unsecured supply most strongly when innovation intensity is high. This is the model counterpart of the empirical triple interaction between monetary easing, non-state banks, and firm innovation. □

3.6 Quantitative Implications

We use the model to quantify the risk-taking channel generated by loan-type heterogeneity. The calibration, described in Appendix C, combines standard banking parameters with moments from Chinese micro data. The exercise focuses on three implications: innovation raises reliance on unsecured credit; monetary easing reallocates unsecured lending toward non-state banks; and macro-prudential policy trades off credit expansion against bank fragility.

In each simulation, banks choose secured and unsecured lending endogenously, allowing the VaR constraint to be either binding or slack. Aggregate investment is pinned down by the firm's optimality condition and loan-market clearing. We then compute bank default probabilities, gross revenue, and loan allocations in equilibrium.

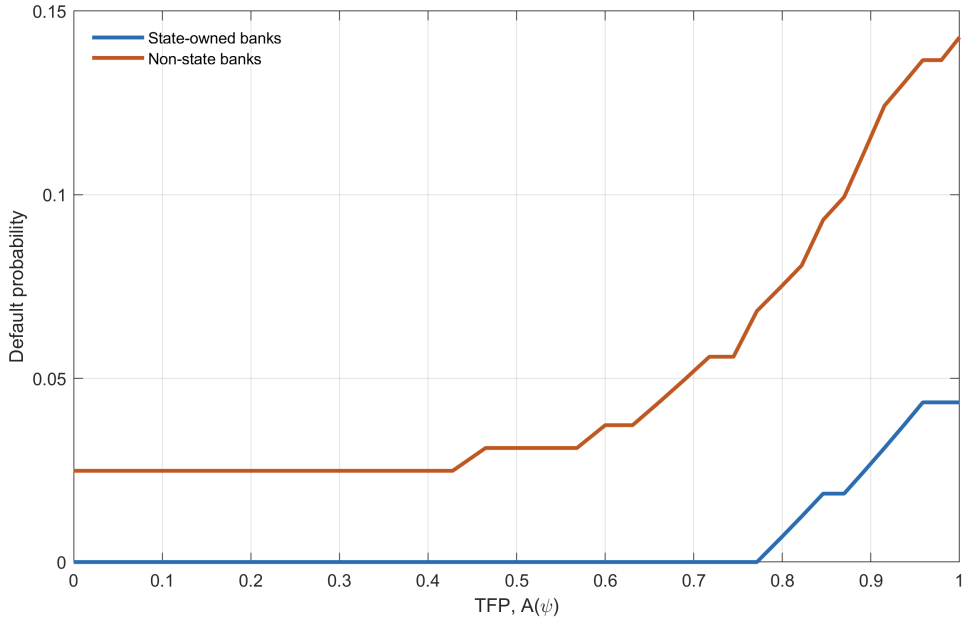


Figure 1: Default probability and project TFP

Notes: This figure plots the correlation between TFP and bank default probability. The horizontal axis is innovation-dependent TFP $A(\psi) = \psi^{0.6}$. For each ψ and bank type, we solve the economy and compute the simulated default probability from bad-state solvency after applying the VaR-implied unsecured tail exposure associated with the innovation state.

Figure 1 shows a stark asymmetry. State-owned banks rely less on market funding, hold larger equity buffers, and face milder unsecured-exposure haircuts. Their default probability therefore remains low across the full range of innovation levels, increasing only modestly when ψ becomes large. By contrast, default probabilities for non-state banks are higher and rise more sharply with $A(\psi)$. The mechanism is direct: a higher innovation share lowers pledgeable collateral and increases equilibrium reliance on unsecured credit. Since unsecured loans recover only partially in the bad state, the projects most closely associated with innovation also expose smaller banks to greater fragility.

Table 6: Response of unsecured lending to a 1 percentage point policy-rate cut

Bank type	% change in ℓ^u	Change in default prob. (p.p.)	% change in gross revenue
State-owned banks	11.17	0.02	7.70
Non-state banks	16.88	0.16	7.70

Notes: This table reports percentage changes in equilibrium unsecured lending, changes in default probability in percentage points, and the percentage change in aggregate gross revenue after a 1 percentage point policy-rate cut. We report percentage changes rather than loan levels because the model is normalized by the initial scale of bank balance sheets.

Table 6 shows that a 1 percentage point cut in the policy rate raises unsecured lending for both ownership groups and increases firm gross revenue. The unsecured-loan response is similar across bank ownership types, while the increase in default probability is larger for non-state banks. This pattern mirrors the empirical evidence and follows directly from Proposition 1: easing compresses the unsecured-secured spread, raises firm demand for unsecured borrowing, and generates a larger fragility response among banks whose tail-state funding pressure is more sensitive to the policy rate.

Figure 2 studies two macro-prudential policy exercises conducted together with a 1 percentage point policy-rate cut. In each panel, the horizontal axis varies one common VaR instrument that applies to both bank types. The left axis reports default probabilities for non-state and state-owned banks, while the right axis reports the change in aggregate gross revenue relative to the pre-cut baseline. Panel A raises the VaR probability threshold $\bar{\alpha}$, loosening the tail-risk requirement. Panel B lowers the VaR haircut on unsecured exposures, ω_μ. Both policies expand unsecured lending and raise output, but they also increase default risk, especially among non-state banks.

Further Discussion. The preceding exercises point to an important policy-relevant mechanism. In recent years, Chinese policymakers have increasingly encouraged banks to expand credit support for technology-oriented and innovative firms. State-owned banks have responded by investing in financial technology, establishing technology-finance branches, accumulating data and patent-related capabilities, and improving their ability to process soft information. These changes can be interpreted as lowering the marginal cost of issuing unsecured loans to innovative firms. Existing studies also suggest that information-technology investment by large banks can reduce loan origination and screening costs, thereby strengthening their competitive advantage in relationship-based and information-intensive lending (Vives and Ye, 2021, Wang et al., 2023).

In the model, we capture such environment by reducing the marginal cost of unsecured lending for state-owned banks ($c_{SOB,u}$). When state-owned banks become more efficient in unsecured lending, they quote lower unsecured-loan rates and attract a larger share of innovative

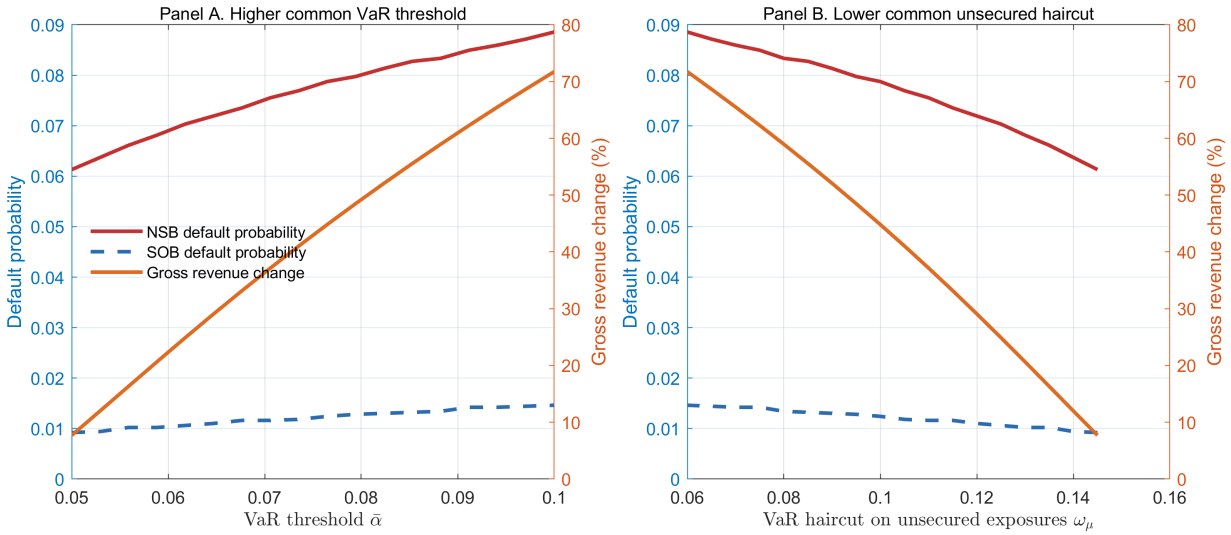


Figure 2: Policy trade-offs after a 1 percentage point policy-rate cut

Notes: This figure compares the outcomes of two macro-prudential policy exercises conducted jointly with expansionary monetary policy. Relative to the baseline economy with a 3.68% policy rate, each panel jointly imposes a 1 percentage point policy-rate cut to 2.68% and varies one macro-prudential instrument for both bank types. Panel A raises the VaR probability threshold $\bar{\alpha}$. Panel B lowers the VaR haircut on unsecured exposures, denoted by ω_μ. The red and blue lines report the simulated default probabilities of non-state and state-owned banks, read against the left vertical axis. The orange line reports the change in aggregate gross revenue relative to the pre-cut baseline and is read against the right vertical axis.

firms' unsecured borrowing. As a result, part of the existing unsecured-loan assets previously intermediated by non-state banks is reallocated toward state-owned banks.

This reallocation has two distinct implications for non-state banks. On the one hand, losing risky unsecured exposures reduces their default probability because their balance sheets become less exposed to low-recovery states. On the other hand, the same process shrinks their loan assets and weakens their lending franchise. Therefore, a decline in default probability should not be interpreted as an unambiguous improvement in financial stability. If non-state banks lose too much of their loan base, their intermediation capacity, relationship capital, and local credit supply may deteriorate.

Figure 3 reports the two primitive outcomes directly, without imposing a reduced-form policy concern function. The horizontal axis measures the reduction in the state-owned-bank unsecured marginal cost. As state-owned banks become more efficient in unsecured lending, non-state banks lose part of their risky unsecured-loan assets. Their default probability declines because risky exposure is transferred away from them, but their unsecured-loan asset loss increases because the same process crowds out their lending relationships. The figure therefore highlights a policy trade-off without requiring arbitrary weights between default risk and franchise loss.

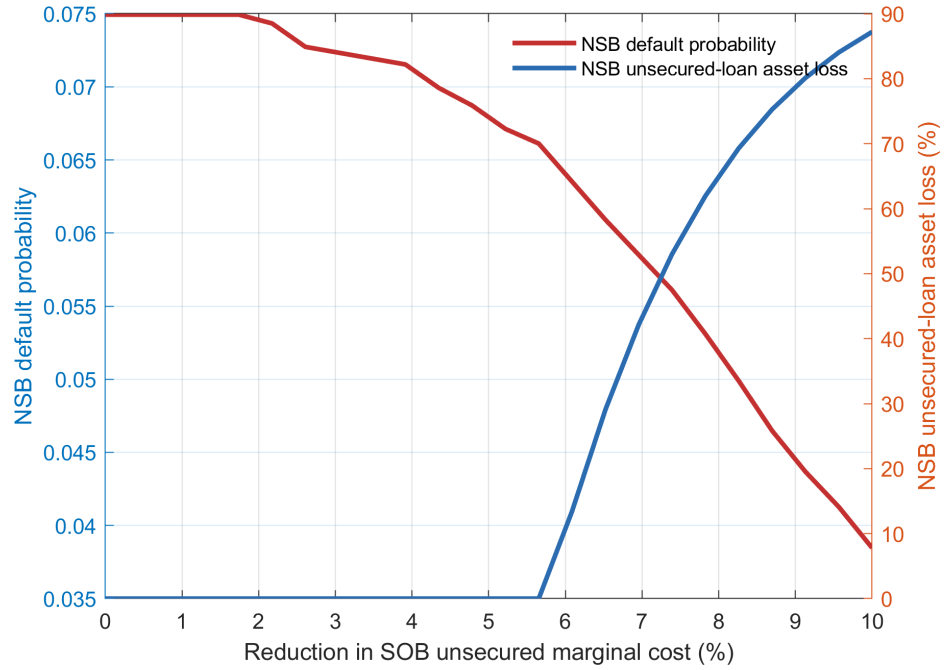


Figure 3: Non-state-bank risk transfer and asset loss under lower state-owned-bank unsecured marginal costs

Notes: This figure varies the reduction in the state-owned-bank unsecured marginal cost after the 1 percentage point policy-rate cut. The red line reports the default probability of non-state banks, read against the left axis. The blue line reports the percentage loss of non-state-bank unsecured-loan assets relative to the post-cut baseline, read against the right axis. Lower state-owned-bank unsecured marginal costs transfer risky unsecured exposure away from non-state banks, reducing their default probability, but also crowd out their unsecured-loan assets.

4 Concluding Remarks

This paper studies how monetary policy affects not only the quantity of bank credit, but also its contractual composition. This margin is especially important in China, where innovation-led growth has become a central policy objective and where small and medium-sized innovative firms continue to rely heavily on bank financing. Because innovative activity creates intangible assets that are difficult to pledge, the relevant credit margin is often unsecured lending rather than collateralized lending.

Using a new firm–bank branch–loan type–quarter data set from NEEQ-listed firms, we document a loan-composition channel of monetary policy. Expansionary shocks increase loan amounts and new loan issuance, but the response is concentrated in unsecured credit loans. This response is stronger for non-state banks than for state-owned banks and is amplified among firms with recent patenting activity. These patterns indicate that monetary easing reallocates credit toward contracts that depend more on borrower cash flow, soft information, and bank risk bearing.

The model rationalizes these facts through the interaction between innovation, collateral scarcity, and bank risk taking. A higher innovation share reduces pledgeable assets and shifts firm demand toward unsecured credit. A policy-rate cut lowers banks' funding costs, relaxes the shadow cost of risk-bearing capacity, and compresses the unsecured-secured spread. Since non-state banks have thinner buffers and operate closer to the VaR boundary, they respond more strongly by expanding unsecured lending. The same mechanism, however, increases their exposure to bad-state recovery risk.

The quantitative exercises highlight the policy trade-off. A one percentage point policy-rate cut raises unsecured lending more for non-state banks and increases aggregate gross revenue, but it also raises non-state-bank default probability. Macroprudential tools that relax or tighten tail-risk constraints affect not only bank fragility but also the composition of credit available to innovative firms. A further exercise shows that improving state-owned banks' ability to supply unsecured credit can lower non-state-bank default risk by transferring risky exposure toward state-owned banks, while at the same time crowding out non-state-bank loan assets and lending relationships. This second margin is relevant for recent policy concerns about small-bank consolidation and local financial stability.

The broader implication is that the bank lending channel should be viewed as a composition channel as well as a quantity channel. Policies that support innovation through bank credit can change which banks take risk and which loan contracts expand. Understanding this allocation is essential for designing monetary and macroprudential policies that support innovation without creating excessive fragility in the banking system.

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Appendix

Appendix A Robustness Checks

Table A.1: Descriptive statistics of the main regression variables

	Mean	SD	Min	Max	Obs.
Dependent variables:					
Loan amount (All loans)	8.013	7.897	0.000	19.383	207,985
Loan amount (Mortgage loans)	7.961	8.043	0.000	19.383	30,555
Loan amount (Pledge loans)	8.774	7.950	0.000	19.383	6,867
Loan amount (Guaranteed loans)	7.830	7.810	0.000	19.383	43,328
Loan amount (Credit loans)	8.528	7.586	0.000	19.383	26,299
Loan amount (Mixed secured loans)	8.393	8.027	0.000	19.383	25,252
New loan (All loans)	0.510	0.500	0.000	1.000	207,985
New loan (Mortgage loans)	0.497	0.500	0.000	1.000	30,555
New loan (Pledge loans)	0.553	0.497	0.000	1.000	6,867
New loan (Guaranteed loans)	0.504	0.500	0.000	1.000	43,328
New loan (Credit loans)	0.562	0.496	0.000	1.000	26,299
New loan (Mixed secured loans)	0.525	0.499	0.000	1.000	25,252
Independent variables:					
Macroeconomic conditions:					
ϵ_{t-1}	-0.042	0.335	-1.862	1.343	207,979
$\widetilde{\epsilon}_{t-1}$	-0.004	0.348	-1.779	1.275	205,987
ΔGDP_{t-1}	1.361	3.144	-10.175	11.363	205,987
Bank characteristics:					
$I(NSB_b)$	0.820	0.384	0.000	1.000	207,985

Notes: This table reports descriptive statistics for the main variables used in the empirical analysis. Loan amount is measured by $lnLoanAmt1$, and new loan is measured by the indicator Ext_Loan. The first block reports these two dependent variables for the full sample and separately by loan type: mortgage, pledge, guaranteed, credit, and mixed secured loans. The second block reports the macroeconomic and bank-type variables used in the baseline and supporting regressions. The non-state-bank indicator $I(NSB_b)$ equals one when $type_SOB \neq 1$ and zero otherwise.

Table A.2: Baseline bank lending channel estimates under alternative monetary shock

	Firm-quarter FE				Firm-loan type-quarter FE			
	Loan Amount		New Loan		Loan Amount		New Loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widetilde{\epsilon}_{t-1}$	0.664***		0.044***		0.591***		0.039***	
	(0.057)		(0.004)		(0.059)		(0.004)	
ΔGDP_{t-1}	-0.030***		-0.002***		-0.031***		-0.002***	
	(0.006)				(0.006)			
$\widetilde{\epsilon}_{t-1} \times I(\text{NSB}_b)$		0.473**		0.032***		0.554***		0.036***
		(0.186)		(0.011)		(0.213)		(0.013)
$I(\text{NSB}_b)$		-10.777***		-0.678***		-10.623***		-0.665***
		(0.106)		(0.006)		(0.117)		(0.007)
$\Delta GDP_{t-1} \times I(\text{NSB}_b)$		-0.019		-0.001		-0.019		-0.001
		(0.016)		(0.001)		(0.019)		(0.001)
Observations	154,358	116,918	154,358	116,918	153,823	92,092	153,823	92,092
R^2	0.077	0.566	0.076	0.571	0.111	0.594	0.111	0.598
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	-	Yes	-	-	-	-	-
Firm-loan type FE	-	-	-	-	Yes	-	Yes	-
Firm-quarter FE	-	Yes	-	Yes	-	-	-	-
Firm-loan type-quarter FE	-	-	-	-	-	Yes	-	Yes

Notes: This table reproduces Table 3 using the alternative monetary policy shock ϵ_{t-1} constructed from Taylor-type policy-rule residuals following Chen et al. (2025). The dependent variables, fixed effects, controls, and sample construction are otherwise identical to those in Table 3. Standard errors are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.3: Loan-type heterogeneity under alternative monetary shock

Dependent Variable:	Loan Amount					New Loan				
Panel A:	Mortgage (1)	Pledge (2)	Guaranteed (3)	Credit (4)	Mixed (5)	Mortgage (6)	Pledge (7)	Guaranteed (8)	Credit (9)	Mixed (10)
$\widetilde{\epsilon}_{t-1}$	0.524***	0.510	0.467***	1.342***	0.450**	0.034***	0.031	0.031***	0.089***	0.030**
	(0.155)	(0.387)	(0.141)	(0.193)	(0.198)	(0.010)	(0.024)	(0.009)	(0.013)	(0.012)
ΔGDP_{t-1}	-0.052***	-0.028	-0.027**	-0.027	-0.007	-0.003***	-0.002	-0.002**	-0.002	-0.000
	(0.015)	(0.029)	(0.013)	(0.017)	(0.017)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	23,661	4,699	30,639	17,407	18,593	23,661	4,699	30,639	17,407	18,593
R^2	0.138	0.154	0.088	0.129	0.119	0.140	0.159	0.087	0.127	0.118
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Variable:	Loan Amount					New Loan				
Panel B:	Mortgage (1)	Pledge (2)	Guaranteed (3)	Credit (4)	Mixed (5)	Mortgage (6)	Pledge (7)	Guaranteed (8)	Credit (9)	Mixed (10)
$\widetilde{\epsilon}_{t-1} \times I(\text{NSB}_b)$	0.030	0.766	-0.751	1.800**	-0.131	0.014	0.052	-0.040	0.117**	-0.014
	(0.586)	(1.855)	(0.598)	(0.777)	(0.734)	(0.035)	(0.110)	(0.037)	(0.050)	(0.045)
$\Delta GDP_{t-1} \times I(\text{NSB}_b)$	-0.049	-0.375***	-0.048	0.009	0.049	-0.003	-0.023***	-0.003	0.001	0.002
	(0.051)	(0.118)	(0.051)	(0.067)	(0.050)	(0.003)	(0.007)	(0.003)	(0.004)	(0.003)
Observations	10,893	1,862	19,537	8,465	10,789	10,893	1,862	19,537	8,465	10,789
R^2	0.653	0.617	0.574	0.628	0.607	0.660	0.626	0.577	0.634	0.611
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reproduces Table 4 using the alternative policy shock ϵ_{t-1}. Panel A reports the average response of each loan type to the alternative shock, and Panel B reports the interaction between the alternative shock and the state-owned-bank indicator within each loan-type sample. All specifications include the same macro controls as in the baseline regressions, and standard errors are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.4: Patent-based innovation heterogeneity under alternative monetary shock

Dependent Variable:	Loan Amount					New Loan				
	Mortgage (1)	Pledge (2)	Guaranteed (3)	Credit (4)	Mixed (5)	Mortgage (6)	Pledge (7)	Guaranteed (8)	Credit (9)	Mixed (10)
$\widetilde{\epsilon}_{t-1} \times I(\text{NSB}_b) \times Patent_{f,t-1}$	0.652	-2.261	0.438	4.812***	-0.041	0.021	-0.105	0.039	0.277***	-0.006
	(1.166)	(3.679)	(1.120)	(1.441)	(1.413)	(0.070)	(0.219)	(0.070)	(0.091)	(0.086)
Observations	10,893	1,862	19,537	8,465	10,789	10,893	1,862	19,537	8,465	10,789
R^2	0.654	0.619	0.574	0.629	0.607	0.660	0.628	0.577	0.634	0.611
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reproduces Table 5 using the alternative policy shock ϵ_{t-1}. $PatentDummy_{i,t-1}$ equals one if the firm filed a patent application in the previous period, and the coefficient of interest is the triple interaction between the alternative shock, the state-owned-bank indicator, and the patent dummy. All columns include firm-quarter fixed effects, lower-order interactions, macro controls, and standard errors in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.5: Credit-loan-share robustness under alternative expansionary shocks

	Credit Loan Share	
	Baseline shock	Alternative shock
	(1)	(2)
$\epsilon_{t-1} \times I(\text{NSB}_b)$	0.034^{***}	0.036^{***}
	(0.011)	(0.011)
$\Delta GDP_{t-1} \times I(\text{NSB}_b)$	-0.040	0.054
	(0.094)	(0.099)
Observations	64,800	64,013
R^2	0.656	0.656
Controls	Yes	Yes
Firm-Quarter FE	Yes	Yes

Notes: The dependent variable is the share of credit loans in a branch's lending to a firm in a quarter. Each column reports a pooled firm–branch–quarter regression with firm-quarter fixed effects. Column (1) uses the baseline expansionary R007 shock, while column (2) uses the alternative expansionary shock constructed from Taylor-rule residuals. The reported coefficients of interest are the interactions between the policy shock and the non-state-bank indicator, together with the corresponding interaction between lagged GDP growth and the non-state-bank indicator. Standard errors are clustered at the bank-branch level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Supporting Evidence on Loan Spread.

The model's pricing mechanism implies that a monetary tightening should widen the spread between unsecured and secured loan rates. To provide supporting evidence on this price margin, we construct an unsecured-secured spread from the loan-level interest-rate variable IR. Since the spread is only defined when unsecured and secured contracts coexist within the same aggregation unit, firm-branch-quarter cells are often sparse. We therefore aggregate the data to the branch-firm-quarter level used in the updated supporting regressions and compute the average interest-rate spread between credit loans and secured loans. The baseline supporting regressions use the quarterly change in *R*007 and the contemporaneous alternative policy shock *mpshock_r*7, together with lagged GDP growth and the interaction with the state-owned-bank indicator.

Table A.6: Monetary tightening and the unsecured-secured loan-rate spread

Dependent Variable:	Loan Spread			
	(1)	(2)	(3)	(4)
ϵ_{t-1}	-0.134***		-0.134***	
	(0.020)		(0.019)	
$\epsilon_{t-1} \times I(\text{NSB}_b)$		-0.328***		-0.254***
		(0.057)		(0.053)
Observations	146,989	146,978	146,059	146,048
R^2	0.189	0.221	0.300	0.340
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	-	Yes	-	Yes
Branch FE	-	-	Yes	Yes

Notes: The dependent variable is the average interest-rate spread between unsecured credit loans and secured loans. Column (1)-(2) uses the quarterly change in *R*007, and column (3)-(4) uses the contemporaneous alternative policy shock *mpshock_r*7. All specifications include the controls embedded in the updated supporting regressions and the fixed effects listed in the table. Standard errors are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.6 provides price-side evidence consistent with the model. In the baseline specifications, an expansionary monetary-policy shock compresses the unsecured-secured spread, meaning that unsecured credit becomes relatively more expensive when policy tightens. This is the price-side counterpart of the composition channel emphasized by the main quantity regressions: when easing lowers banks' effective funding cost, the relative price of unsecured credit compresses and firms rely more heavily on that loan type. The interaction with the state-owned-bank indicator is negative, which is consistent with the idea that state-owned banks adjust this spread less aggressively than non-state banks. We interpret this appendix table as supporting rather than stand-alone evidence, leaving the quantity-based composition results as the paper's primary empirical findings.

Appendix B Details on Model Derivation

Since bank under the good state is always solvent, we can rewrite the expected profit in Equation (15) as the following form:

$$V_{it} = \max_{\{r^u_{it}, \ell^u_{it}, \ell^s_{it}, G_{it}\}} \left\{ \chi \pi^H_{it} + (1-\chi) \mathbb{I}_{it} \bar{\pi}^L_{it} \right\},$$

where $\bar{\pi}^L_{it}$ replaces ω_{it} in (13) with the expected recovery value $\bar{\omega}_\tau \equiv E_\tau[\omega_{it}]$.

Proposition 2. Let F_τ denote the recovery-shock distribution for banks of type τ, and define the lower-tail recovery quantile $\omega_{\alpha,\tau} \equiv F_\tau^{-1}(\bar{\alpha})$. The VaR constraint in Equation (14) is equivalent to the deterministic solvency condition

$$(r^s_t - c_{\tau,s})\ell^s_{it} + (\omega_{\alpha,\tau} - c_{\tau,u})\ell^u_{it} - c_F - r^D_{\tau t} b_{it} - f_t G_{it} + e_{it} \geq 0. \tag{B.1}$$

Unlike a standard capital-adequacy constraint, Equation (B.1) depends on bad-state cash flow. Equity relaxes the constraint through the buffer term e_{it}, while unsecured credit tightens the constraint when the lower-tail recovery value $\omega_{\alpha,\tau}$ is low relative to the unsecured lending cost.

Proof. Write the bad-state profit as the sum of a deterministic component and the stochastic unsecured recovery term:

$$\pi_{it}^{L} = X_{it} + \omega_{it}\ell_{it}^{u},$$

where

$$X_{it} \equiv (r_t^s - c_{\tau,s})\ell_{it}^{s} - c_{\tau,u}\ell_{it}^{u} - c_F - r_{\tau t}^{D} b_{it} - f_t G_{it}.$$

Since only the bad state can trigger insolvency, Equation (14) becomes

$$\Pr(X_{it} + \omega_{it}\ell_{it}^{u} + e_{it} < 0) \leq \bar{\alpha}.$$

For $\ell_{it}^{u} > 0$, this is equivalent to

$$\Pr\left(\omega_{it} < -\frac{X_{it} + e_{it}}{\ell_{it}^{u}}\right) \leq \bar{\alpha}.$$

Because F_τ is continuous and strictly increasing on the relevant support, the probability condition holds if and only if

$$-\frac{X_{it} + e_{it}}{\ell_{it}^{u}} \leq F_\tau^{-1}(\bar{\alpha}) \equiv \omega_{\alpha,\tau}.$$

Multiplying by $\ell_{it}^{u} > 0$ and rearranging gives (B.1). If $\ell_{it}^{u} = 0$, the VaR condition reduces to the deterministic requirement $X_{it} + e_{it} \geq 0$, which is the limiting case of (B.1). □

Given above Proposition, we write down the Lagrangian of bank's problem in (15):

$$\begin{aligned}\mathcal{L}_{it} =& \chi\pi_{it}^{H} + (1-\chi)\mathbb{I}_{it}\bar{\pi}_{it}^{L} + \lambda_{it}\left(e_{it} + b_{it} + G_{it} - \ell_{it}^{s} - \ell_{it}^{u}\right) \\ &+ \mu_{it}\left[(r_t^s - c_{\tau,s})\ell_{it}^{s} + (\omega_{\alpha,\tau} - c_{\tau,u})\ell_{it}^{u} - c_F - r_{\tau t}^{D} b_{it} - f_t G_{it} + e_{it}\right],\end{aligned}$$

The first-order conditions with respect to market funding G_{it}, secured loan ℓ_{it}^{s} and unsecured loan ℓ_{it}^{u} are:

$$[G_{it}]. \quad \lambda_{it} = f_t\left(S_{it} + \mu_{it}\right) \tag{B.2}$$

$$[\ell_{it}^{s}]. \quad \left(S_{it} + \mu_{it}\right)\left(r_t^s - c_{\tau,s}\right) = \lambda_{it} \tag{B.3}$$

$$[\ell_{it}^{u}]. \quad \chi\left[\frac{\partial(r_{it}^{u}\ell_{it}^{u})}{\partial\ell_{it}^{u}} - c_{\tau,u}\right] + (1-\chi)\mathbb{I}_{it}(\bar{\omega}_\tau - c_{\tau,u}) + \mu_{it}(\omega_{\alpha,\tau} - c_{\tau,u}) - \lambda_{it} = 0. \tag{B.4}$$

Combining the first order conditions (B.2) and (B.3) gives the competitive secured-loan pricing equation

$$r_t^s = c_{\tau,s} + f_t. \tag{B.5}$$

For unsecured lending, the bank internalizes the downward-sloping demand curve. From

(10), the inverse demand curve implies

$$r_{it}^u = r_{\tau t}^u \left(\frac{\ell_{it}^u}{L_{\tau t}^u} \right)^{-1/\varepsilon},$$

so the marginal revenue from unsecured lending is

$$\frac{\partial (r_{it}^u \ell_{it}^u)}{\partial \ell_{it}^u} = \frac{\varepsilon - 1}{\varepsilon} r_{it}^u.$$

Plugging above results into (B.4) yields:

$$\chi \left[\frac{\varepsilon - 1}{\varepsilon} r_{it}^u - c_{\tau,u} \right] + (1 - \chi) \mathbb{I}_{it} (\bar{\omega}_\tau - c_{\tau,u}) + \mu_{it} (\omega_{\alpha,\tau} - c_{\tau,u}) - \lambda_{it} = 0. \tag{B.6}$$

Substituting (B.2) into (B.6) yields

$$r_{it}^u = \frac{\varepsilon}{\varepsilon - 1} \left[c_{\tau,u} + \frac{f_t (S_{it} + \mu_{it}) - (1 - \chi) \mathbb{I}_{it} (\bar{\omega}_\tau - c_{\tau,u}) - \mu_{it} (\omega_{\alpha,\tau} - c_{\tau,u})}{\chi} \right]. \tag{B.7}$$

Subtracting (B.5) from (B.7) gives the unsecured-secured spread:

$$\begin{aligned} r_{it}^u - r_t^s = & \frac{\varepsilon}{\varepsilon - 1} \left[c_{\tau,u} + \frac{f_t (S_{it} + \mu_{it}) - (1 - \chi) \mathbb{I}_{it} (\bar{\omega}_\tau - c_{\tau,u}) - \mu_{it} (\omega_{\alpha,\tau} - c_{\tau,u})}{\chi} \right] \\ & - (c_{\tau,s} + f_t). \end{aligned} \tag{B.8}$$

Therefore, we obtain the response of the spread to the policy rate shown in (16):

$$\frac{\partial}{\partial f_t} (r_{it}^u - r_t^s) = \underbrace{\frac{\varepsilon}{\varepsilon - 1} \frac{S_{it} + \mu_{it}}{\chi} - 1}_{\text{direct funding-cost effect}} + \underbrace{\frac{\varepsilon}{\varepsilon - 1} \frac{f_t + c_{\tau,u} - \omega_{\alpha,\tau}}{\chi} \frac{\partial \mu_{it}}{\partial f_t}}_{\text{VaR shadow-cost effect}}. \tag{B.9}$$

Appendix C Details on Numerical Computation

In the quantitative implementation, we discipline this distribution by specifying the joint law of equity and leverage:

$$\log e_{it} \sim \mathcal{N}(1, \sigma_e^2), \qquad \log Lev_{it} = \rho_{e,L} \log e_{it} + \nu_{it}, \qquad \nu_{it} \sim \mathcal{N}(\mu_L, \sigma_L^2),$$

where $Lev_{it} \equiv e_{it}/(e_{it} + b_{it})$. Given (e_{it}, Lev_{it}), deposits are pinned down by

$$b_{it} = e_{it} \left(\frac{1 - Lev_{it}}{Lev_{it}} \right).$$

This specification generates heterogeneity in both bank size and funding structure while preserving the empirical fact that smaller banks tend to operate with thinner buffers.

Calibration. The numerical exercise combines parameters calibrated from Chinese bank-level, loan-level, and aggregate data with standard values from the banking literature. The

initial distribution of each bank's equity and deposits, $\{e(i), b(i)\}$, is exogenously given. We discipline this distribution by calibrating the joint distribution of equity $e(i)$ and leverage $Lev(i) \equiv e(i)/(e(i)+b(i))$. Specifically, we assume

$$\log(e(i)) \sim \mathcal{N}(1, \sigma_e^2), \qquad \log(Lev(i)) = \rho_{e,L} \log(e(i)) + \mathcal{N}(\mu_L, \sigma_L^2).$$

Following Wang et al. (2023), we set $\sigma_e = 1.415$, $\rho_{e,L} = -0.253$, $\mu_L = -2.170$, and $\sigma_L = 0.427$.

The firm's innovation-dependent productivity follows a parsimonious concave mapping,

$$A(\psi) = \psi^{0.6}. \tag{C.10}$$

This specification preserves the key assumption that the productivity gain from innovation is increasing but concave in the R&D share. We set the discount factor to $\beta = 0.99$, a standard quarterly value. The success probability is $\chi = 0.95$, consistent with the low non-performing loan ratios reported for SME and unsecured-loan portfolios by listed banks. The capital share in production is $\alpha = 0.5$, following Liu et al. (2021). We set the collateral parameter to $\theta = 0.55$, equal to the average debt-to-asset ratio of Chinese A-listed firms over 2014Q1–2024Q4.

We calibrate loan-pricing parameters from loan-level interest rates. The gross policy-rate factor is $f = 1 + 3.68\%$, where 3.68% is the average LPR during the sample period. The average secured-loan rate is 5.20%. Under the competitive secured-loan pricing condition $1 + p^s = c_s + f$, this implies

$$c_s = (1 + 0.0520) - (1 + 0.0368) = 0.0152.$$

The average unsecured credit-loan rate is 4.92%.[7] We therefore set

$$c_u = c_s - \Delta_c = 0.0124,$$

where Δ_c is pinned down by the observed spread between average secured and unsecured loan rates. The fact that $c_u < c_s$ should not be interpreted as unsecured loans being safer. In the model, the risk premium on unsecured credit also depends on the project success probability, the default state, and the tightness of the VaR constraint.

The within-type elasticity of substitution across individual banks is $\varepsilon = 4.961$, following Wang et al. (2023). The fixed operating cost is $c_F = 0.027$, following Wang et al. (2022). The elasticity of substitution across bank ownership types in the unsecured-loan aggregator is $\sigma_u = 2.5$, consistent with standard values used in the banking literature. According to the average deposit rates in our sample period, we set $r^D_{SOB} = 0.018$ and $r^D_{NSB} = 0.0215$. Finally, we set the baseline VaR probability threshold to $\bar{\alpha} = 0.05$, so that the regulatory constraint corresponds to a 5% lower-tail violation probability in the recovery-shock distribution.

[7] The average credit-loan rate is 4.22% for state-owned banks and 5.39% for non-state banks.

Table C.7: Baseline calibration for the numerical algorithm

Parameter	Value	Interpretation
β	0.99	Discount factor
χ	0.95	Project success probability
α	0.50	Capital share in production
θ	0.55	Pledgeable share of tangible capital
$A(\psi)$	$\psi^{0.6}$	Concave productivity mapping
f	$1 + 3.68\%$	Average gross LPR during the sample period
c_s	0.0152	Secured-loan marginal cost wedge
c_u	0.0124	Unsecured-loan marginal cost wedge
c_F	0.027	Fixed operating cost
r_S^D	0.018	SOB deposit cost
r_N^D	0.0215	NSB deposit cost
σ_u	2.5	CES elasticity across bank types for unsecured loans
ε	4.961	Within-type CES elasticity across individual banks
$\bar{\alpha}$	0.05	Common VaR lower-tail probability threshold
σ_e	1.415	Dispersion of log equity
$\rho_{e,L}$	-0.253	Equity-leverage correlation in the initial distribution
$\mu_L,\ \sigma_L$	$-2.170,\ 0.427$	Mean and dispersion of log leverage

Notes: This table reports the structural and data-calibrated parameters used in the baseline quantitative exercise. Purely numerical implementation choices, such as grid sizes and auxiliary smoothing parameters, are not reported. The loan-cost parameters are expressed as marginal cost wedges under the gross-rate pricing convention $1 + p^m = c_m + f$.

Throughout the numerical exercise, the exogenous objects are the firm innovation state ψ, project TFP $A(\psi)$, policy and regulatory parameters, bank-type-specific cost parameters, and bank capital. The endogenous objects are firm capital K, secured and unsecured borrowing ℓ^s, ℓ^u, loan prices p^s and $p^u(i)$, the unsecured-secured spread, the VaR shadow value μ_i, and the implied default probabilities and gross revenue.

Numerical Algorithm.

1. Given K, compute: $L^S = \theta(1-\psi)K$, $L^u = [1 - \theta(1-\psi)]K$.

2. Since secured loan market is competitive, we have $1 + p^s = c_s + f$

3. Use firm FOC to solve aggregate p^u:

$$\big[1 + \chi A(\psi)\big] g'(K) = \theta(1-\psi)(1+p^s) + \chi\big[1 - \theta(1-\psi)\big](1+p^u). \tag{C.11}$$

   where we have:

$$1 + p^u = \frac{[1 + \chi A(\psi)] g'(K) - \theta(1-\psi)\,(1+p^s)}{\chi[1 - \theta(1-\psi)]}.$$

4. Guess p^u_{SOB}, and plug into the CES price-index equation:

$$p^u = \left[\omega_u \left(p^u_{SOB}\right)^{1-\sigma_u} + (1-\omega_u)\left(p^u_{NSB}\right)^{1-\sigma_u}\right]^{1/(1-\sigma_u)}.$$

to back out p^u_{NSB}.

5. Compute type-level unsecured demand:

$$L^u_\tau = \omega_\tau \left(\frac{p^u_\tau}{p^u}\right)^{-\sigma_u} L^u$$

6. For each bank i, solve both VaR cases: slack $\mu_i = 0$, binding $\mu_i > 0$. Keep feasible candidates and choose the one with highest limited-liability value.

   - For each bank i with endowment $(e(i), b(i))$, solve the bank problem. Given initial equity and deposits, for each $G(i)$ on a grid, evaluate candidate loan pairs $(\ell^u(i)_\tau, \ell^s(i)_\tau)$.
   - compute loan prices from demand curve $p^u(i)_\tau = p^u_\tau (l^u_\tau(i)/L^u_\tau)^{-1/\epsilon}$
   - compute bad-state profit: $\pi^L(i)$
   - Determine survival indicator $\mathbb{I}(i)$
   - **VaR binding case,** $\mu(i) > 0$ by plugging the FOC of bank secured loan supply condition, bank balance sheet, we solve $l^u(i)$:

$$\begin{aligned} &\pi^L(i) + e(i) - \omega_{\tau,u} l^u(i) = 0 \\ \implies &(1 + p^s - c_{\tau,s}) l^s(i) - (c_{\tau,u} + \omega_{\tau,u}) l^u(i) - c_F - (1 + r^D_\tau) b(i) - fG(i) + e(i) = 0 \\ \implies &l^u(i) = \frac{f(e(i) + b(i)) - c_F - (1 + r^D_\tau) b(i) + e(i)}{c_{\tau,u} + \omega_{\tau,u} + f} \end{aligned}$$

     Then $l^s(i)$ is obtained from the balance sheet condition.
     Next, we keep the loan pairs such that the bank unsecured loan supply condition indeed holds for $\mu(i) > 0$.

$$\mu_i = \frac{\chi \left[1 + \frac{\varepsilon - 1}{\varepsilon} p^u_i - c_{\tau,u}\right] - (1 - \chi)\mathbb{I}_i c_{\tau,u} - fA_i}{f + c_{\tau,u} + \omega_{\tau,u}}.$$

   - **slack case** $\mu(i) = 0$**.** Then the unsecured loan FOC implies:

$$p^u_\tau(i) = \frac{\varepsilon}{\varepsilon - 1}\left[c_{\tau,u} - 1 + \frac{(1 - \chi)\mathbb{I}_i c_{\tau,u} + fA_i}{\chi}\right].$$

     Then we obtain $\ell^u(i)$ from the individual demand curve:

$$\ell^u(i) = L^u_\tau \left(\frac{p^u(i)_\tau}{p^u_\tau}\right)^{-\varepsilon}$$

     Then, $l^s(i) = e(i) + b(i) + G(i) - \ell^u(i)$. Next, we keep this slack solution only if $\pi^L(i) + e(i) - \omega_{\tau,u} l^u(i) > 0$
   - compute expected profit:

$$V_\tau = \chi \max\{\pi^H_\tau, 0\} + (1 - \chi)\max\{\pi^L_\tau, 0\},$$

and keep the highest one as the optimal choice of $(l^u(i), l^s(i), G(i))$.

7. Aggregate individual unsecured supply:

$$L^u_\tau = \left[\int_{i\in\tau} \ell^u_\tau(i)^{\frac{\varepsilon-1}{\varepsilon}} di\right]^{\frac{\varepsilon}{\varepsilon-1}}$$
$$p^u_\tau = \left[\int_{i\in\tau} p^u_\tau(i)^{1-\varepsilon} di\right]^{\frac{1}{1-\varepsilon}}$$

8. Iterate on p^u_{SOB} until individual-bank aggregation equals type-level demand.

To endogenize aggregate capital, we add the firm's first-order condition and unsecured-loan market-clearing conditions. The unknowns become $(K, p^u_{SOB}, p^u_{NSB})$. Given a trial triple, we compute the aggregate unsecured price index, implied firm demand for K, type-level unsecured loan demand, individual-bank optimal supplies under the two VaR regimes, and the resulting aggregate unsecured supply by ownership. We then update $(K, p^u_{SOB}, p^u_{NSB})$ until

$$L^u_{SOB,s} = L^u_{SOB,d}, \qquad L^u_{NSB,s} = L^u_{NSB,d},$$

and

$$[1 + \chi A(\psi)]g'(K) - \theta(1-\psi)(1+p^s) - \chi[1-\theta(1-\psi)](1+p^u) = 0.$$

At the converged fixed point, aggregate capital is endogenous, while bank default probabilities are computed as the share of grid banks for which $\pi^L(i) < 0$.