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Zheng Liu
Federal Reserve Bank of San Francisco

Mark M. Spiegel
Federal Reserve Bank of San Francisco

Jingyi Zhang
Shanghai University

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TARGETED RESERVE REQUIREMENTS FOR MACROECONOMIC STABILIZATION

ZHENG LIU, MARK M. SPIEGEL, AND JINGYI ZHANG

Abstract. We study the effectiveness of targeted reserve requirements (RR) as a policy tool for macroeconomic stabilization. Targeted RR adjustments were implemented in China during both the 2008-09 global financial crisis and the recent COVID-19 pandemic. We develop a model in which firms with idiosyncratic productivity can borrow from two types of banks—local or national—to finance working capital. National banks provide liquidity services, while local banks have superior monitoring technologies, such that both types coexist. Relationship banking is modeled in terms of a fixed cost of switching lenders, and banks choose to switch only under sufficiently large shocks. Reducing RR on local banks boosts leverage and aggregate output, whereas reducing RR on national banks has an ambiguous output effect. Following a large recessionary shock, a targeted RR policy that reduces RR for local banks relative to national banks can lower costs of switching lenders, stabilizing macroeconomic fluctuations. However, targeting RR in that manner also boosts local bank leverage, increasing risks of default and related liquidation losses. Our model's mechanism is supported by bank-level empirical evidence.

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Liu: Federal Reserve Bank of San Francisco; Email: Zheng.Liu@sf.frb.org. Spiegel: Federal Reserve Bank of San Francisco; Email: Mark.Spiegel@sf.frb.org. Zhang: School of Economics, Shanghai University of Finance and Economics, China; Email: zhang.jingyi@mail.shufe.edu.cn. The research is partly supported by the National Natural Science Foundation of China Project Number 72203139 and 71633003. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System.

I. Introduction

Recent macro-prudential policy initiatives include attempts to mitigate financial instability through differential capital requirements on large and small banks. For example, the Basel III framework imposes higher capital requirements on large and systemically important banks than small banks. In practice, some central banks have implemented macro-prudential initiatives through targeted reserve requirements (RR). For example, Brazil has reduced RR to induce large banks to extend liquidity to small banks through asset purchases (e.g. Tovar, Garcia-Escribano and Martin (2012)). Brazil's RR system also partly exempts small banks on a variety of deposits (Glocker and Towbin (2015)).

The People's Bank of China (PBOC) has also implemented targeted RR adjustments. It cut RR more aggressively for small and medium-sized banks than large national banks during the 2008 global financial crisis. The PBOC then again widened the RR wedge between small and large banks in response to the COVID-19 pandemic (see Figure 1). However, unlike the macro-prudential considerations that have driven the debate on bank-specific, time-varying capital requirements and Brazil's targeted RR policies, the PBOC's RR adjustments appear to have been motivated by the desire to stabilize macroeconomic fluctuations.

In this paper, we study the effectiveness of targeted RR adjustments as a policy tool for macroeconomic stabilization. We present a model that features two types of banks: national and local. National banks face lower funding costs, but local banks have better monitoring technologies (e.g., because of superior information about local borrowers), allowing both types to coexist in equilibrium. Firms face idiosyncratic productivity shocks and they borrow from banks to finance working capital. Low productivity firms choose to default and costly state verification gives rise to credit spreads, as in Bernanke, Gertler and Gilchrist (1999). A firm in a relationship with a bank (local or national) can switch lenders, but this switch incurs a fixed cost. As a result, firms only switch banks when they face sufficiently large shocks—such as the 2008 financial crisis or the COVID-19 pandemic.

Our model also includes a government, which sets RR policy which can differ across the two types of banks, and provides deposit insurance for all savers, financed by lump-sum taxes.

We then calibrate the model to Chinese data and study the implications of targeted RR adjustments over business cycles. To better understand the transmission mechanism of targeted RR adjustments, we posit two extreme cases of bank switching costs: in one case, firms can switch banks freely; while in the other case, firms cannot switch banks and credit markets are effectively segmented between firms borrowing from local or national banks.

Under our calibration, reducing RR for local banks (denoted by τ_l) unambiguously raises aggregate output in both cases. In particular, at a lower τ_l, local banks face lower funding

FIGURE 1. China's required reserve (RR) ratios for banks of different sizes.

costs, reducing their loan interest rate. Since local banks are more efficient in monitoring and thus charge a lower credit spread, the shift of lending from national to local banks expands firm leverage and increases output. The expansionary effect is larger when firms can switch banks freely than when firms face segmented credit markets.

RR adjustments for national banks (τ_n) have different implications for the two cases. In the case where firms can switch banks freely, cutting τ_n has two opposing effects on aggregate output. At the intensive margin, the reduction in τ_n lowers national bank lending rates, raising leverage by firms that borrow from national banks. However, at the extensive margin, the decline in τ_n induces some firms to switch from local banks to national banks. Since local banks are more efficient in monitoring, the switch of lending toward national banks raises the average credit spread and reduces aggregate leverage. Under our calibration, the extensive-margin effect dominates when firms can switch banks freely, such that cutting τ_n reduces aggregate output. However, in the case where firms cannot switch banks, cutting τ_n only has intensive margin effects, leading to higher firm leverage and boosting aggregate output.

We also study the implications of targeted RR adjustments for macroeconomic stabilization over the business cycle. We postulate a targeted RR policy rule, under which the central bank can adjust two types of required reserve ratios, one for local banks and the other for national banks, to respond to changes in output gap measured by deviations of real GDP from its trend. We solve for optimal welfare-maximizing targeted RR rules for technology shocks of different sizes. We find that a decline in real GDP calls for a more aggressive RR cut on local banks than on national banks only in environments with sufficiently large shocks.

This policy implication arises from the difference in business cycle sensitivities between national banks and local banks. In our model, local banks, due to their monitoring advantages, have higher steady state leverage and face higher default probabilities. Thus, lending by local banks is more sensitive to an adverse shock than that by national banks. If the adverse shock is sufficiently large, then firms that originally borrowed from local banks would pay the fixed cost of switching, and borrow from national banks instead. This switching would then disrupt existing bank relationships and amplify the recession. In this case, a larger cut of RR for local banks helps mitigate the costly bank-switching and improves macroeconomic stability and welfare.

Our model's mechanism and predictions are supported by empirical evidence. We use Chinese bank-level annual data for the period 2008 to 2021 to examine how lending of banks of different sizes responds differently to local shocks and how this difference in sensitivity varies with the size of the shocks. We find that, all else being equal, a decline in local GDP reduces the lending of small banks more than that of medium-sized banks. Moreover, this difference is larger in periods with large shocks. This evidence lends empirical support to our model's mechanism.

II. Related literature

Our work is related to the literature on the positive and normative implications of capital or reserve requirement policies. The literature highlights a tradeoff between prudential and macroeconomic goals. den Heuvel (2008) demonstrates that restricting bank lending through capital requirements raises borrowing costs, which reduces welfare. Nicolò, Gamba and Lucchetta (2014) demonstrate that this tradeoff results in an interior solution for optimal bank capital requirements in a dynamic model aimed at discouraging excessive bank risk taking under deposit insurance. Several studies extend this analysis to consider this tradeoff under both capital and reserve requirements (e.g. Gorton, Lewellen and Metrick (2012) and Christiano and Ikeda (2016)).[1]

A recent paper by Corbae and D'Erasmo (2019) considers heterogeneity across banks by size in the form of a single representative "big bank" and a large number of atomistic small banks that take interest rates as given. While their paper focuses primarily on capital

[1]The robustness of this result has been called into question, as some models suggest that when deposit rates can adjust, raising capital requirements can actually increase bank lending (e.g. Begenau (2020)).

requirement policies, it obtains heterogeneous responses by large and small banks to changes in capital requirements and possible welfare enhancement through targeted heterogeneous changes in capital controls.[2] They also consider differential capital requirements between large and small banks.

Changes in reserve requirements have similarly been found to discourage lending activity [e.g. Loungani and Rush (1995)], but as a result will also have implications for macroeconomic stability. They can then be used as a tool to complement monetary policy in macroeconomic stabilization. Alper, Binici, Demiralp, Kara and Özlü (2018) demonstrate that RR increases, by reducing the liquidity of the banking system, can serve as a vehicle for reducing domestic credit and economic activity. Similarly, Brei and Moreno (2019) demonstrate in Latin American bank-level data increases in reserve requirements can reduce lending activity without increasing deposit rates, and thereby serve as a useful vehicle for stemming disruptive capital inflows. The literature documents the extensive use of reserve requirement policy as a tool for macroeconomic stabilization in emerging market economies [e.g. Montoro and Moreno (2011), Federico, Vegh and Vuletin (2014), and Mora (2014)], with China making particularly frequent reserve requirement adjustments (Chang, Liu, Spiegel and Zhang (2019)). Agénor, Alper and da Silva (2018) demonstrate in a DSGE framework for a small open economy that a counter-cyclical reserve requirement rule can mitigate financial and macroeconomic instability.

Finally, our paper is specifically related to the literature on the potential allocative effects of adjustments to the supply of or demand for reserves. On the supply side, Kashyap and Stein (2000) demonstrate that, for example, removal of reserves by the monetary authority can drag on bank lending behavior. Moreover, they demonstrate that these changes disproportionately impact on lending by less liquid smaller banks in the financial system. On the demand side, usually driven by changes in reserve requirements, Górnicka (2016) demonstrate that increases in RR can influence the share of bank intermediation relative to "shadow banks".

III. The model

The economy is populated by a continuum of infinitely lived households. The representative household consumes homogeneous goods produced by firms using capital and labor. Firms face working capital constraints. Each firm finances wages and rental payments using both internal net worth and external debt. Following Bernanke et al. (1999), we assume that external financing is subject to a costly state verification problem. In particular, while

[2]Corbae and D'Erasmo (2019) do consider the implications of liquidity requirements, which can be interpreted as similar to minimum reserve requirements.

each firm can observe its own idiosyncratic productivity shocks, a lender needs to pay a monitoring cost in the event of firm default.

There are two types of banks, national and local, with a continuum of each type indexed by $i \in [0,1]$. Both types of banks intermediate between households (savers) and firms (borrowers) and face perfect competition in the lending and deposit markets. The two types of banks differ in four dimensions: (1) national banks provide better liquidity services and face lower funding costs; (2) local banks have better monitoring technologies, reflecting relationship banking; (3) deposits in both types of banks are protected by deposit insurance, but treatment under bankruptcy differs by bank type. Given bankruptcy, local banks are liquidated while national banks are recapitalized; and (4) bank types face distinct required reserve ratios.

III.1. **Households.** There is a continuum of infinitely-lived and identical households with a unit mass. The representative household has the expected utility function

$$U = \mathrm{E}\sum_{t=0}^{\infty}\beta^t\left[\ln(C_t) - \Psi_h\frac{H_t^{1+\eta}}{1+\eta} + \Psi_n\ln(D_{n,t})\right], \tag{1}$$

where E is an expectations operator, C_t denotes consumption, H_t denotes labor hours, and $D_{n,t}$ denotes deposits in national banks. The parameter $\beta \in (0,1)$ is a subjective discount factor, $\eta > 0$ is the inverse Frisch elasticity of labor supply, $\Psi_h > 0$ reflects the disutility of working, and $\Psi_n > 0$ captures the preferences for liquidity services provided by national banks through their deposit products.

The household faces the sequence of budget constraints

$$C_t + I_t + D_{nt} + D_{lt} = w_tH_t + r_t^kK_{t-1} + R_{n,t-1}^dD_{n,t-1} + R_{l,t-1}^dD_{l,t-1} + T_t, \tag{2}$$

where I_t denotes the capital investment, $D_{l,t}$ the deposits in local banks, w_t the real wage rate, r_t^k the real rental rate on capital and K_{t-1} the level of the capital stock at the beginning of period t. $R_{n,t-1}^d$ and $R_{l,t-1}^d$, respectively, denote the gross interest rate on deposits in national banks and local banks from period $t-1$ to period t. T_t denotes the lump-sum transfers from the government and earnings received from firms based on the household's ownership share.

The capital stock evolves according to the law of motion

$$K_t = (1-\delta)K_{t-1} + \left[1 - \frac{\Omega_k}{2}\left(\frac{I_t}{I_{t-1}} - g_I\right)^2\right]I_t, \tag{3}$$

where we have assumed that changes in investment incur an adjustment cost, the size of which is measured by the parameter Ω_k. The constant g_I denotes the steady-state growth rate of investment.

The household chooses C_t, H_t, D_{nt}, D_{lt}, I_t, and K_t to maximize (1), subject to the constraints (2) and (3). The optimization conditions are summarized by the following equations:

$$w_t = \frac{\Psi H_t^{\eta}}{\Lambda_t}, \tag{4}$$

$$1 = \mathrm{E}_t \beta R_{nt}^d \frac{\Lambda_{t+1}}{\Lambda_t} + \Psi_n \frac{1}{\Lambda_t D_{n,t}}, \tag{5}$$

$$1 = \mathrm{E}_t \beta R_{lt}^d \frac{\Lambda_{t+1}}{\Lambda_t}, \tag{6}$$

$$\begin{aligned} 1 &= q_t^k \left[1 - \frac{\Omega_k}{2} \left(\frac{I_t}{I_{t-1}} - g_I \right)^2 - \Omega_k \left(\frac{I_t}{I_{t-1}} - g_I \right) \frac{I_t}{I_{t-1}} \right] \\ &\quad + \beta \mathrm{E}_t q_{t+1}^k \frac{\Lambda_{t+1}}{\Lambda_t} \Omega_k \left(\frac{I_{t+1}}{I_t} - g_I \right) \left(\frac{I_{t+1}}{I_t} \right)^2, \end{aligned} \tag{7}$$

$$q_t^k = \beta \mathrm{E}_t \frac{\Lambda_{t+1}}{\Lambda_t} [q_{t+1}^k (1-\delta) + r_{t+1}^k]. \tag{8}$$

where Λ_t denotes the Lagrangian multiplier for the budget constraint (2), Λ_t^k is the Lagrangian multiplier for the capital accumulation equation (3), and $q_t^k \equiv \frac{\Lambda_t^k}{\Lambda_t}$ is Tobin's q.

III.2. **Firms.** There is a continuum of competitive firms that produce the homogeneous consumption good using capital and labor as inputs. Firms face idiosyncratic productivity and working capital constraints. In particular, firms pay wage bills and capital rents prior to observing their productivity. Firms finance working capital using both their internal net worth and external debt borrowed from banks. After the realizations of idiosyncratic productivity shocks, firms choose whether or not to default on bank loans. There are two types of banks: national (type n) and local (type l). In each period, a firm chooses to borrow from one bank, while a bank can lend to multiple firms.

III.2.1. *Production.* Consider a representative firm that borrows from a type-b bank $b \in \{n, l\}$. The firm produces a homogeneous consumption good $Y_{b,t}$ using capital $K_{b,t}$, household labor $H_{b,ht}$, and entrepreneurial labor $H_{b,et}$, with the production function

$$Y_{b,t} = A_t \omega_{b,t} (K_{b,t})^{1-\alpha} \left[(H_{b,et})^{1-\theta} H_{b,ht}^{\theta} \right]^{\alpha}, \tag{9}$$

where A_t denotes aggregate productivity, and the parameters $\alpha \in (0,1)$ and $\theta \in (0,1)$ are input elasticities in the production technology. The term $\omega_{b,t}$ is an idiosyncratic productivity shock that is i.i.d. across firms and time, and is drawn from the distribution $F(\cdot)$ with a non-negative support.

Aggregate productivity A_t contains a deterministic trend g^t and a stationary component A_t^m so that $A_t = g^t A_t^m$. The stationary component A_t^m follows the stochastic process

$$\ln A_t^m = \rho_a \ln A_{t-1}^m + \epsilon_{at}, \tag{10}$$

where $\rho_a \in (-1, 1)$ is a persistence parameter, and the term ϵ_{at} is an i.i.d. innovation drawn from a log-normal distribution $N(0, \sigma_a)$.

The firm finances the costs of labor and capital inputs using its own beginning-of-period net worth $N_{b,t}$ and bank loans $B_{b,t}$, subject to the working capital constraint

$$N_{b,t} + B_{b,t} = w_t H_{b,ht} + w_t^e H_{b,et} + r_t^k K_{b,t}. \tag{11}$$

where w_t^e denotes the real wage rate of entrepreneurial labor. Here, we assume that entrepreneurial labor and household labor are both perfectly mobile across firms and that the working capital to be financed includes wage bills for both types of labor, in addition to capital rental payments.

Cost-minimizing implies the conditional factor demand functions

$$w_t H_{b,ht} = \alpha\theta(N_{b,t} + B_{b,t}), \tag{12}$$

$$w_t^e H_{b,et} = \alpha(1-\theta)(N_{b,t} + B_{b,t}), \tag{13}$$

$$r_t^k K_{b,t} = (1-\alpha)(N_{b,t} + B_{b,t}). \tag{14}$$

Substituting these optimal choices of input factors in the production function (9), we obtain $Y_{b,t} = \omega_{b,t}\tilde{A}_t(N_{b,t} + B_{b,t})$, where $\tilde{A}_t$ denotes the average rate of return on the working capital financed by both internal funds and external debt. Specifically, we have

$$\tilde{A}_t = A_t \left(\frac{1-\alpha}{r_t^k}\right)^{1-\alpha} \left[\left(\frac{\alpha(1-\theta)}{w_t^e}\right)^{1-\theta} \left(\frac{\alpha\theta}{w_t}\right)^{\theta}\right]^{\alpha}. \tag{15}$$

III.2.2. *Optimal loan contracts.* Following Bernanke et al. (1999), we assume that lenders can only observe a borrower's realized investment return at a cost. In the event that a firm defaults on its debt, the lender can obtain the firm's output, net of a monitoring cost that equals a fraction m_b of the output (with $b \in \{n, l\}$). To capture relationship banking, we assume that the monitoring cost facing local banks is lower than that facing national banks (i.e., $m_n > m_l > 0$).

To cover the expected cost of firm default, a bank of type b charges a gross interest rate $Z_{b,t}$ on its loans. Under this financial arrangement, there is a cutoff level of productivity $\bar{\omega}_{b,t}$, such that firms with productivity below the cutoff (i.e., $\omega_{b,t} < \bar{\omega}_{b,t}$) will choose to default. The cutoff level of productivity $\bar{\omega}_{b,t}$ is determined by the break-even condition

$$\bar{\omega}_{b,t} \equiv \frac{Z_{b,t} B_{b,t}}{\tilde{A}_t(N_{b,t} + B_{b,t})}, \tag{16}$$

such that firms with productivity at the cutoff level earns zero net profit. The probability of default is therefore given by $F(\overline{\omega}_{b,t})$, the cumulative density of idiosyncratic productivity evaluated at $\bar{\omega}_{b,t}$.

If the firm's productivity is above the cutoff level $\bar{\omega}_{b,t}$ (with the probability $1-F(\overline{\omega}_{b,t})$), then the firm repays the bank loan at the contractual interest rate $Z_{b,t}$ and keeps the remaining profit. The expected income for a firm that borrows from a type-b bank is therefore given by

$$\begin{aligned}
&\int_{\overline{\omega}_{b,t}}^{\infty} \tilde{A}_t \omega_{b,t}(N_{b,t}+B_{b,t})dF(\omega) - (1-F(\overline{\omega}_{b,t}))Z_{b,t}B_{b,t} \\
&= \tilde{A}_t(N_{b,t}+B_{b,t})[\int_{\overline{\omega}_{b,t}}^{\infty} \omega dF(\omega) - (1-F(\overline{\omega}_{b,t}))\overline{\omega}_{b,t}] \\
&\equiv \tilde{A}_t(N_{b,t}+B_{b,t})h(\overline{\omega}_{b,t}), \qquad (17)
\end{aligned}$$

where $h(\overline{\omega}_{b,t})$ is the firm's share of investment income under the loan contract.

Under the optimal loan contract characterized by $B_{b,t}$ and $\bar{\omega}_{b,t}$, the expected income for the lender is given by

$$\begin{aligned}
&(1-F(\overline{\omega}_{b,t}))Z_{b,t}B_{b,t} + \int_0^{\overline{\omega}_{b,t}} \{(1-m_b)\tilde{A}_t\omega(N_{b,t}+B_{b,t})\}dF(\omega) \\
&= \tilde{A}_t(N_{b,t}+B_{b,t})\{[(1-F(\overline{\omega}_{b,t}))\overline{\omega}_{b,t} + (1-m_b)\int_0^{\overline{\omega}_{b,t}} \omega dF(\omega)\} \\
&\equiv \tilde{A}_t(N_{b,t}+B_{b,t})g_b(\overline{\omega}_{b,t}), \qquad (18)
\end{aligned}$$

where $g_b(\overline{\omega}_{b,t})$ is the bank's share of investment income. This optimal loan contract takes into account the resource of monitoring, such that

$$h(\overline{\omega}_{b,t}) + g_b(\overline{\omega}_{b,t}) = 1 - m_b \int_0^{\overline{\omega}_{b,t}} \omega dF(\omega). \qquad (19)$$

The optimal contract is then a pair $(\bar{\omega}_{b,t}, B_{b,t})$ chosen at the beginning of period t to maximize the borrower's expected period t income,

$$\tilde{A}_t(N_{b,t}+B_{b,t})h(\overline{\omega}_{b,t}) \qquad (20)$$

subject to the lender's participation constraint

$$\tilde{A}_t(N_{b,t}+B_{b,t})g_b(\overline{\omega}_{b,t}) \geq R_{b,t}B_{b,t}. \qquad (21)$$

where $R_{b,t}$ denotes the average loan return required by a type-b bank.

The optimizing conditions for the contract characterize the relation between the leverage ratio and the productivity cut-off

$$\frac{N_{b,t}}{B_{b,t}+N_{b,t}} = -\frac{g_b'(\overline{\omega}_{b,t})}{h'(\overline{\omega}_{b,t})}\frac{\tilde{A}_t h(\overline{\omega}_{b,t})}{R_{b,t}}. \qquad (22)$$

III.2.3. *Bank choice.* In each period, a borrower has the option of switching banks subject to a switching cost.[3] Denote by $\mathcal{B}_t(i)$ the bank type chosen by firm i in period t. Switching to a different lender incurs a cost that equals a fraction $\gamma > 0$ of the firm's net worth, reflecting the fixed cost of setting up a new lender-borrower relation. Given this cost, a firm would choose to switch lenders only when they are switching to a different type of banks. Thus, if firm i switches lenders in period t, then the type of the bank in the new relation would be different from the type in the previous period (i.e., $\mathcal{B}_t(i) \neq \mathcal{B}_{t-1}(i)$).

We now characterize firms' bank choice problem. At the end of each period, a firm survives with probability ξ_e. If the firm does not survive, then its terminal net worth would be distributed to the households who own the firm. The firm chooses a bank type to maximize the present value of the firm's net worth

$$\mathbb{V}_t(\nu_{t-1}(i), \mathcal{B}_{t-1}(i)) \equiv \max_{\mathcal{B}_t(i)} \mathrm{E}_t \sum_{j=0} (1-\xi_e)\xi_e^j \beta^j \Lambda_{t+j} \nu_{t+j}(i), \tag{23}$$

where $\nu_t(i)$ denotes the firm's net worth at the end of the period t.

Denote by $ROE_{b,t}$ the ex-ante return on equity for a firm that borrows from a type-b bank. In particular,

$$ROE_{b,t} \equiv h(\overline{\omega}_{b,t}) \frac{\tilde{A}_t(N_{b,t} + B_{b,t})}{N_{b,t}}, \tag{24}$$

where $(\bar{\omega}_{b,t}, B_{b,t})$ are the solution to the optimal contract problem described in Section III.2.2.

If the firm does not switch banks (i.e., $\mathcal{B}_t(i) = \mathcal{B}_{t-1}(i)$), then its present value is given by the Bellman equation

$$\mathbb{V}_t(\nu_{t-1}(i), \mathcal{B}_{t-1}(i)) = (1-\xi_e) ROE_{\mathcal{B}_t(i),t} \nu_{t-1}(i) + \xi_e \beta \mathrm{E}_t \mathbb{V}_{t+1}(ROE_{\mathcal{B}_t(i),t} \nu_{t-1}(i), \mathcal{B}_t(i)), \tag{25}$$

If the firm switches bank type (i.e., $\mathcal{B}_t(i) \neq \mathcal{B}_{t-1}(i)$), then it needs to pay the switching cost γ, with the firm's present value given by the Bellman equation

$$\mathbb{V}_t(\nu_{t-1}(i), \mathcal{B}_{t-1}(i)) = (1-\xi_e)(ROE_{\mathcal{B}_t(i),t} - \gamma)\nu_{t-1}(i) + \xi_e \beta \mathrm{E}_t \mathbb{V}_{t+1}((ROE_{\mathcal{B}_t(i),t} - \gamma)\nu_{t-1}(i), \mathcal{B}_t(i)). \tag{26}$$

To solve the bank type decision problem, we guess that the value function $\mathbb{V}_t(\nu_{t-1}(i), b)$ is linear in $\nu_{t-1}(i)$:

$$\mathbb{V}_t(\nu_{t-1}(i), b) \equiv V_{b,t} \nu_{t-1}(i), \tag{27}$$

[3] Asymmetric information between borrowers and banks create barriers for borrowers to switch banks and, therefore, borrowers may incur switching costs when setting up a close tie with a bank (e.g. Boot, 2000). Switching costs have also appear to be prevalent in the Chinese bank loan market. For example, Yin and Matthews (2018) demonstrate that in a sample of Chinese firms and banks over the period 1999-2012 and found that around half of firms with bank credit history have switched to a new bank in the sample, and small, opaque firms are less likely to switch than large, transparent firms.

where $V_{b,t}$ is then given by,

$$V_{b,t} = \max\{[(1-\xi_e) + \xi_e \beta \mathrm{E}_t V_{b,t+1}] ROE_{b,t}, [(1-\xi_e) + \xi_e \beta \mathrm{E}_t V_{b',t+1}](ROE_{b',t} - \gamma)\}. \tag{28}$$

where $b' \neq b$ denotes the bank type in period $t+1$ that differs from the bank type b in period t.

The optimal choice of bank type for a firm that borrows from a type-b in previous period ($\mathcal{B}_{t-1}(i) = b$) is summarized by following conditions:

$$\begin{cases} \mathcal{B}_t(i) = b', \quad \text{if } \bar{V}_{b',t}(ROE_{b',t} - \gamma) > \bar{V}_{b,t} ROE_{b,t}, \\ \mathcal{B}_t(i) \in \{b, b'\}, \quad \text{if } \bar{V}_{b',t}(ROE_{b',t} - \gamma) = \bar{V}_{b,t} ROE_{b,t}, \\ \mathcal{B}_t(i) = b, \quad \text{if } \bar{V}_{b',t}(ROE_{b',t} - \gamma) < \bar{V}_{b,t} ROE_{b,t}. \end{cases} \tag{29}$$

Here, $\bar{V}_{b,t}$ denotes the firm's expected present value per unit of its end-of-period net worth and is given by

$$\bar{V}_{b,t} = (1-\xi_e) + \xi_e \beta \mathrm{E}_t V_{b,t+1}. \tag{30}$$

Eq. (29) identifies three possible ranges for a firm's optimal choice of bank type. In the first range, the firm switches from its previous bank of type b to a new bank of type b' because the benefit of switching to the new bank type b' sufficiently exceeds the benefit of borrowing from its previous bank type b ($\bar{V}_{b',t} ROE_{b',t} - \bar{V}_{b,t} ROE_{b,t} > \gamma \bar{V}_{b',t}$). In the second range, the benefit of switching exactly equals the benefit of not switching ($\bar{V}_{b',t} ROE_{b',t} - \bar{V}_{b,t} ROE_{b,t} = \gamma \bar{V}_{b',t}$) so that the firm is indifferent between switching and not switching banks ($\mathcal{B}_t(i) \in \{b, b'\}$). In the third range, the firm does not switch banks because the benefit of doing so is less than the switching cost ($\bar{V}_{b',t} ROE_{b',t} - \bar{V}_{b,t} ROE_{b,t} < \gamma \bar{V}_{b',t}$).

III.2.4. *Aggregate wealth accumulation.* Given the firm survival probability ξ_e, the average lifespan of a firm is $\frac{1}{1-\xi_e}$. The managers (i.e., entrepreneurs) of the exiting firms are replaced by an equal mass $(1-\xi_e)$ of new managers, so that the population size of entrepreneurs stays constant.

Managers of all firms—new or continuing—supply entrepreneurial labor at the competitive wage rate w_{et}. New managers use their entrepreneurial labor income as start-up funds. For simplicity, we assume that a manager's supply of entrepreneurial labor is proportional to the firm's net worth such that the bank switching cost (γ) only affects the dynamic equilibrium without changing the steady state allocations. The economy has one unit of aggregate supply of entrepreneurial labor supply (i.e., $H_{et} = 1$).

We assume that all firms, including continuing firms and new entrants, have an ongoing relationship with their current bank. Thus, firms do not need to pay an additional cost if they choose to borrow from the same bank in the next period.

Denote by $\bar{N}_{b,t}$ the end-of-period aggregate net worth of all firms financed with a bank of type b in period t, which consists of profits earned by surviving firms, net of bank switching costs (if any), plus entrepreneurial labor income. The net worth is given by

$$\bar{N}_{b,t} = \xi_e[\tilde{A}_t h(\overline{\omega}_{b,t})(N_{b,t} + B_{b,t}) - \gamma \max\{N_{b,t} - \bar{N}_{b,t-1}, 0\}] + \frac{N_{b,t}}{N_{n,t} + N_{l,t}} w_t^e H_{et}. \tag{31}$$

where $N_{b,t} - \bar{N}_{b,t-1}$, if positive, measures the aggregate net worth of all firms that switch to a bank of type b from another bank, thereby incurring a switching cost.

Denote by $\bar{N}_t$ the aggregate net worth of all firms by the end of period t, which is given by

$$\bar{N}_t = \bar{N}_{n,t} + \bar{N}_{l,t}. \tag{32}$$

Since $N_{b,t}$ is the aggregate net worth of firms that choose a bank of type b at the beginning of period t, we have

$$N_{l,t} + N_{n,t} = \bar{N}_{t-1}, \tag{33}$$

Figure 2 illustrates the timeline of firms' financing decisions and the evolution of firms' aggregate net worth. In the beginning of period t, firms choose the types of banks (national or local) from which they borrow. Then firms and banks choose the optimal loan contracts before observing idiosyncratic productivity shocks. Production takes place after the realization of productivity shocks. Firms then decide whether they want to repay the loans or default. At the end of the period, some firms survive while others exit, and the managers of exiting firms are replaced by an equal mass of new entrepreneurs. Aggregate net worth of firms that borrow from each type of banks is also determined at the end of the period.[4]

III.3. **Banks.** There are two types of commercial banks, national banks (type n) and local banks (type l), competing with each other in the loan market. There is a unit continuum of banks for each type. Consider a type-b bank i, with $b \in \{n, l\}$, $i \in [0, 1]$. At the beginning of each period t, the bank obtains household deposits $d_{b,t}(i)$ at interest rate $r^d_{b,t}(i)$ subject to the demand schedule,

$$d_{b,t}(i) = \left(\frac{r^d_{b,t}(i)}{R^d_{b,t}} \right)^{\theta_d} D_{b,t}, \tag{34}$$

The above demand schedule is derived under the assumption that the unit of type-b ($b \in \{n, l\}$) deposits held by the households is a composite CES basket of differentiated deposits supplied by individual banks, with elasticity of substitution equal to $-\theta_d$, with

[4] Appendix A provides more details on how the aggregate net worth of firms that borrow from each type of banks changes (from $\bar{N}_{b,t-1}$ to $N_{b,t}$) following bank switching at the beginning of each period.

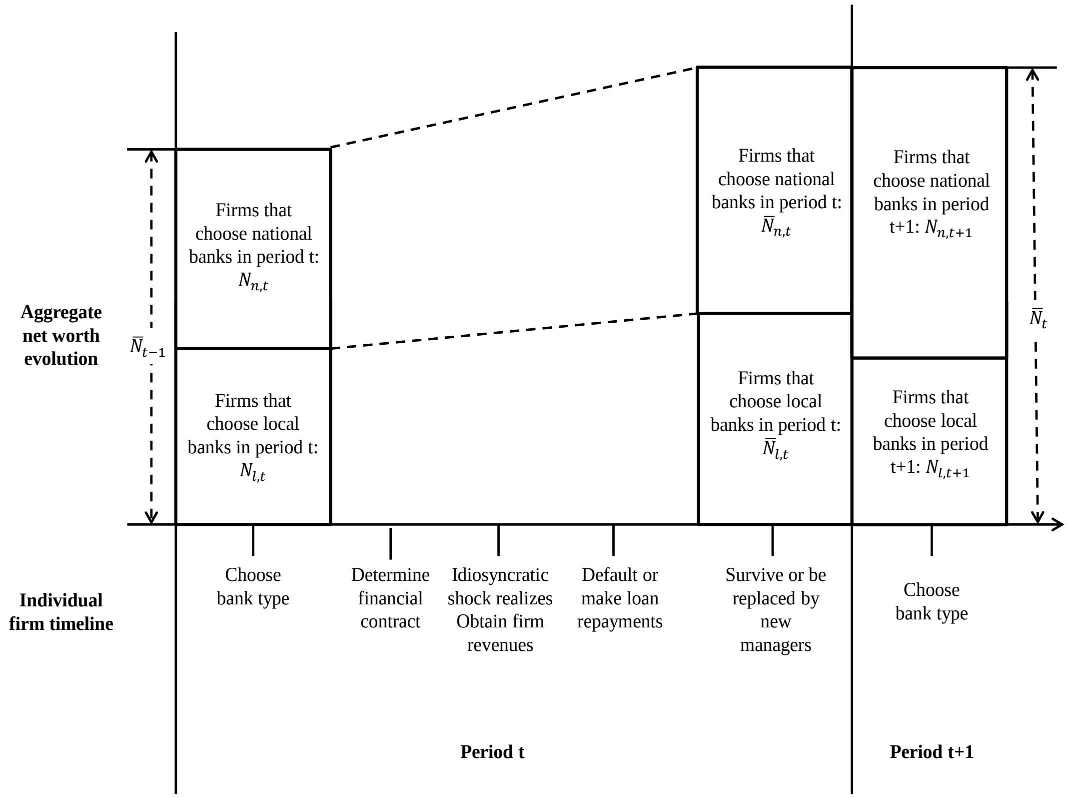

FIGURE 2. The timeline of individual firms' financing decisions and the evolution of the aggregate net worth of firms.

$\theta_d > 0$.[5] Under this assumption, the aggregate-individual relations of deposits and deposit rates are given by,

$$D_{b,t} = \left[\int_0^1 d_{bt}(i)^{\frac{\theta_d+1}{\theta_d}} di \right]^{\frac{\theta_d}{\theta_d+1}}, \tag{35}$$

$$R^d_{b,t} = \left[\int_0^1 r^d_{b,t}(i)^{1+\theta_d} di \right]^{\frac{1}{1+\theta_d}}, \tag{36}$$

Each bank is required to hold a fraction $\tau_{b,t}$ of its deposits as reserves with no interest earnings. It can lend the remaining funds to firms. The bank faces the flow-of-funds

[5]We assume monopsonistic competition on the deposit market to ensure the existence of solvent banks in our model's equilibrium. Otherwise, perfection competition would force banks' expected profit to be zero, which, together with the limited liability assumption, implies that all banks become insolvent and earn zero profits in the equilibrium. This assumption is a widely-used modeling device to capture the existence of market power in the banking industry. For a similar approach, see, for example, Ulate (2021), Angelini, Neri and Panetta (2014), and Gerali, Neri, Sessa and Signoretti (2010). Alternatively, one could ensure the existence of solvent banks in the equilibrium by imposing borrowing constraints on banks, as in Gertler and Kiyotaki (2010), which won't change our key model mechanisms.

constraint

$$b_{b,t}(i) = (1 - \tau_{b,t})d_{b,t}(i), \tag{37}$$

where $b_{b,t}(i)$ denotes the amount of loans.

The bank faces default risks on firm loans. These loans generate a random return $\epsilon_{bt}R_{b,t}$ at the end of period t, where $R_{b,t}$ denotes the average return on the loan and ϵ_{bt} denotes an idiosyncratic loan quality shock observed after the loans have been granted. The loan quality shock ϵ_{bt} is drawn from the distribution $\Phi(\cdot)$ with a nonnegative support, and it is i.i.d. across banks and time. We normalize the average loan quality shock to one (i.e., $E(\epsilon_{bt}) = 1$) .

The bank's gross return from its asset holdings by the end of period t is then given by,

$$\tau_{b,t}d_{b,t}(i) + \epsilon_{bt}R_{b,t}b_{b,t}(i)$$

With a sufficiently low value of realized ϵ_{bt}, the bank would be insolvent because the gross return from its asset holdings would be inadequate to service its deposit obligations. We define $\bar{\epsilon}_{b,t}(i) \geq 0$ as the threshold value of loan quality, below which the bank would be insolvent. The insolvency threshold is given by

$$\bar{\epsilon}_{b,t}(i) = \frac{r^d_{b,t}(i)d_{b,t}(i) - \tau_{b,t}d_{b,t}(i)}{R_{b,t}b_{b,t}(i)}. \tag{38}$$

The government provides full deposit insurance, such that households do not suffer any losses when a bank default occurs. For simplicity, we assume that the government does not charge a deposit insurance premium on banks; instead, it levies lump-sum taxes on households to compensate the depositors in the event of a bank default. The government also treats national banks differently from local banks in the event of a default. An insolvent national bank would be fully recapitalized (financed by lump-sum taxes on households), whereas an insolvent local bank would be liquidated. Liquidating a local bank incurs a resource cost equal to a fraction μ_l of a local bank's gross return from its asset holdings.

The presence of deposit insurance distorts banks' lending decisions. Under limited liability, a bank's expected profit at the end of period t is given by

$$\pi_t(i) = \int_{\bar{\epsilon}_{b,t}}^{+\infty} \left[\tau_{b,t}d_{b,t}(i) + \epsilon_{bt}R_{b,t}b_{b,t}(i) - r^d_{b,t}(i)d_{b,t}(i)\right] d\Phi(\epsilon_{bt}). \tag{39}$$

The bank chooses deposits $d_{b,t}$ and loans $b_{b,t}$ to maximize the expected profit (39), subject to the flow-of-funds constraint (37) and the deposit demand schedule (34). The bank's optimizing decisions imply that[6]

$$\frac{\theta_d}{\theta_d+1}\left[\frac{\int_{\bar{\epsilon}_{b,t}(i)}^{+\infty}\epsilon_{bt}d\Phi(\epsilon_{bt})}{1-\Phi(\bar{\epsilon}_{b,t}(i))}R_{b,t}(1-\tau_{b,t})+\tau_{b,t}\right]=r_{b,t}^d(i). \tag{40}$$

Thus, the marginal return on lending conditional on bank solvency equals the marginal cost of funding. The cost of an extra unit of deposits equals the deposit interest rate. By taking an extra unit of deposits, the bank can lend out $1-\tau_{b,t}$ units of loans under the reserve requirements. The bank earns the return on lending only if it remains solvent, with the probability of solvency given by $1-\Phi(\bar{\epsilon}_{b,t}(i))$. At the end of the period, the bank obtains the expected return on lending (conditional on solvency) plus the required reserves. With market powers in the deposit markets, the bank"marks down" the deposit interest rate, such that the deposit rate $r_{b,t}^d(i)$ is lower than the expected return on lending (since $\frac{\theta_d}{\theta_d+1}<1$). In a symmetric equilibrium, we have $r_{b,t}^d(i)=R_{b,t}^d$ for all i and for $b\in\{n,l\}$.

Under limited liability, a bank's internal valuation of loans reflects only the returns on those loans with sufficiently high quality (i.e., with $\epsilon_{b,t}(i)\geq\bar{\epsilon}_{b,t}$). This leads to excessive lending. Eq. (38) shows that the excessive lending problem can be mitigated by raising the reserve requirements $\tau_{b,t}$. By reducing the loanable funds, an increase in $\tau_{b,t}$ would reduce over-lending and thus lower the probability of bank insolvency. In the extreme case where $\tau_{b,t}$ is sufficiently high, the probability of bank insolvency can be reduced to zero (i.e., $\bar{\epsilon}_{b,t}=0$), eliminating excessive lending distortions.

III.4. **Market clearing and equilibrium.** In equilibrium, the markets for goods, intermediate goods, capital and labor inputs, and loans all clear.

Goods market clearing implies that

$$\begin{aligned}Y_t &= C_t+I_t+\sum_{b=n,l}\tilde{A}_t(N_{b,t}+B_{b,t})m_b\int_0^{\bar{\omega}_{bt}}\omega dF(\omega)\\ &\quad+\mu_l\int_0^{\bar{\epsilon}_{l,t}}\epsilon_{l,t}R_{l,t}b_{l,t}d\Phi(\epsilon_{l,t})+\sum_{b=n,l}\gamma\max\{N_{b,t}-\bar{N}_{b,t-1},0\}. \end{aligned}\tag{41}$$

where $Y_t=Y_{nt}+Y_{lt}$ denotes gross output, which is used for financing consumption and investment spending and for covering the costs of monitoring defaulting firms, liquidating insolvent local banks, and switching borrowers. We define GDP as the aggregate value added, which equals gross output net of the resource costs for monitoring firms, liquidating

[6]Under monoposonistic competition in the deposit markets, the solvency threshold $\bar{\epsilon}_{b,t}$ is a function of the individual bank's deposits and loans. However, Eq. (38) implies that the flow profit (i.e., the term within the squared brackets in Eq. (39) evaluated at $\bar{\epsilon}_{b,t}$ is zero, such that the partial derivatives of $\bar{\epsilon}_{b,t}$ with respect to the bank-level decision variables vanish from the first order conditions.

insolvent local banks, and switching borrowers. Thus, real GDP corresponds to the sum of consumption and investment and is given by

$$GDP_t = C_t + I_t. \tag{42}$$

Factor market clearing implies that

$$K_{t-1} = K_{n,t} + K_{l,t}, \quad H_t = H_{n,ht} + H_{l,ht}. \tag{43}$$

The loans market clearing implies that,

$$B_{n,t} = \int_0^1 b_{n,t}(i)di, \quad B_{l,t} = \int_0^1 b_{l,t}(i)di. \tag{44}$$

IV. Calibration

We solve the model numerically based on calibrated parameters. Where possible, we calibrate the model parameters to match moments in Chinese data. Five sets of parameters need to be calibrated. The first set are those in the household decision problem. These include β, the subjective discount factor; η, the inverse Frisch elasticity of labor supply; Ψ_h, the utility weight on leisure; Ψ_n, the utility weight on liquidity services; θ_d, the negative elasticity of substitution across individual bank deposits; δ, the capital depreciation rate; and Ω_k, the investment adjustment cost parameter. The second set includes parameters for firms and financial intermediaries. These include g, the average trend growth rate; $F(\cdot)$, the distribution of the firm idiosyncratic productivity shock, respectively; α, the capital share in the production function; θ, the share of labor supplied by the household; m_b, the monitoring cost by type b banks; ξ_e, the survival rates of firm managers; and $\Phi(\cdot)$, the distribution of the idiosyncratic loan quality shock. The third set of parameters are those in government policy and the shock processes, which includes $\bar{\tau}_n$ and $\bar{\tau}_l$, the average RR on national banks and local banks, respectively; μ_l, the cost of liquidating insolvent local banks; and ρ_a and σ_a, the persistence and standard deviation of the productivity shock. Table 1 summarizes the calibrated parameter values.

A period in the model corresponds to one quarter. We set the subjective discount factor to $\beta = 0.9975$. We set $\eta = 1$, implying a Frisch labor elasticity of 1, which lies in the range of empirical studies. We calibrate $\Psi_h = 7.5$ such that the steady state value of labor hour is about one-third of total time endowment (which itself is normalized to 1). We calibrate the utility weight on liquidity services $\Psi_n = 0.005$ and the negative elasticity of substitution $\theta_d = 163$ such that national banks' lending rate $4(R_n - 1)$ and deposit rate $4(R_n^d - 1)$, respectively, equals 6% per annum and 3% per annum, which is consistent with the historical average of the policy lending rate and policy deposit rate in China. For the parameters in the capital accumulation process, we calibrate $\delta = 0.035$, implying an annual depreciation rate of 14%, which also matches Chinese data. We set the investment adjustment cost parameter $\Omega_k = 5$, which lies in the range of empirical estimates of DSGE models (Christiano, Eichenbaum and Evans, 2005; Smets and Wouters, 2007).

For the technology parameters, we set the steady-state balanced growth rate to $g = 1.0125$, implying an average annual growth rate of 5%. We assume that firms' idiosyncratic productivity shocks are drawn from a unit-mean log normal distribution such that the logarithm of ω follows a normal distribution $N(-\sigma^2/2, \sigma^2)$. We calibrate the distribution parameter σ to match empirical estimates of cross-firm dispersions of TFP in the manufacturing industries in China. In particular, Hsieh and Klenow (2009) estimated that the annualized standard deviation of the logarithm of TFP across Chinese manufacturing firms is about 0.63 in 2005. This implies that $\sigma = 0.63/2$. We calibrate the labor income share to $\alpha = 0.5$, consistent with empirical evidence in Chinese data (Brandt, Hsieh and Zhu, 2008; Zhu, 2012).

For the parameters associated with financial frictions, we follow Bernanke et al. (1999) and set the monitoring cost for local banks to $m_l = 0.1$. We set the managerial labor share to $1-\theta = 0.04$, such that entrepreneurs' labor income accounts for 2% of aggregate output. We jointly calibrate the monitoring cost for national bank (m_n) and the firm survival probability (ξ_e) to target a steady-state loan default ratio of 0.10 and a steady-state share of local bank loans of 0.5. These targeted moments match, respectively, the average delinquency ratio on business loan reported by the People's Bank of China and the average share of business loans granted by small and medium-sized banks (including city commercial banks and rural commercial banks) reported by the Banking Regulatory Commission of China.

For the parameters associated with the banking sector, we assume that the idiosyncratic shocks to loan quality (ϵ_b) are drawn from a log normal distribution with a unit mean, such that $\ln(\epsilon_b)$ follows the normal distribution $N(-\sigma_b^2/2, \sigma_b)$. We set $\sigma_b = 0.01/2$ to match the annualized standard deviation of loan delinquency ratios across individual banks of 0.01 in the data. Firms' bank switching cost is set to $\gamma = 0.009$ to match the volatility of the share of firm loans granted by local banks of 0.01 in the data.

For the government policy parameters, we calibrate the steady-state RR to 0.15 for both national banks and local banks. We have less guidance for calibrating the parameter μ_l, the cost of liquidating insolvent local banks. We set $\mu_l = 0.03$ as a benchmark, implying that the liquidation cost accounts for a small share (0.1%) of aggregate output in the steady state. For the parameters related to the shock process, we follow the standard business cycle literature and set the persistence parameter to $\rho_a = 0.95$ for the technology shocks. In Section VI, We consider a variety of shock sizes for each shock to examine how the size of the shocks affect the effectiveness of targeted RR policy.

Table 1. Calibrated values.

Variable	Description	Value
	A. Households	
β	Subjective discount factor	0.9975
η	Inverse Frisch elasticity of labor supply	1
Ψ_h	Weight of disutility of working	7.5
Ψ_n	Weight of utility of liquidity services	0.005
θ_d	Negative elasticity of substitution of deposits	163
δ	Capital depreciation rate	0.035
Ω_k	Capital adjustment cost	5
	B. Firms and financial intermediaries	
g	Steady state growth rate	1.0125
σ	Volatility parameter in log normal distribution of firm idiosyncratic shocks	0.315
α	Capital income share	0.5
m_n	National bank monitoring cost	0.2
m_l	Local bank monitoring cost	0.1
ξ_e	Firm manager's survival rate	0.86
θ	Share of household labor	0.96
σ_b	Volatility parameter in log normal distribution of bank idiosyncratic shocks	0.005
γ	Bank switching cost	0.009
	C. Government policy and shock processes	
$\bar{\tau}_n$	RR on National bank	0.15
$\bar{\tau}_l$	RR on Local bank	0.15
μ_l	Liquidation cost of local banks	0.03
ρ_z	Persistence of TFP shock	0.95

V. Transmission mechanism for RR shocks

We first use the calibrated model to explore the dynamics of the economy following unexpected changes in RR policies. In particular, we consider an unexpected cut in the RR for each bank type:

$$\tau_{b,t} = \tau_b + \epsilon^b_{\tau,t}. \tag{45}$$

To illustrate the role of switching costs when borrowers switch banks in the transmission mechanism of RR policies, we compare the impulse response to two types of RR changes in two cases: one case with no switching costs ($\gamma = 0$), the other case with infinite switching costs ($\gamma = +\infty$).

V.1. **Reducing local bank RR.** Figure 3 displays the impulse responses to a 1% negative RR shock on local banks ($\epsilon^l_{\tau,t} = -0.01$). Reducing τ_l lowers the local banks' funding cost and thus their required return on lending. However, reducing τ_l also leads local banks to hold less riskless bank reserves and raise local banks' probability of insolvency. The increase in local banks' insolvency probability raises the overvaluation distortion on local bank lending and eases their lending terms. As local banks expand their credit supply, the national banking sector shrinks and the liquidity services provided by national banks become more valuable. This reduces the national bank deposit rate and the probability of national bank insolvency.

In the case with no switching costs ($\gamma = 0$), reducing τ_l lowers the interest charged by local banks' on lending, and leads some firms to switch their borrowing from national banks to local banks. Since local banks have superior monitoring technology and are willing to accept riskier borrowers, the shift to local banks raises average firm leverage and default ratios. As a result, firms' leverage and output are increased. However, firm default costs and local bank bankruptcy costs also increase.

In the case with infinite switching costs ($\gamma = +\infty$), reducing τ_l also lowers the local banks' required return on lending, and firms again respond by increasing their leverage and raising output. However, compared with the case with no switching costs ($\gamma = 0$), this stimulative impact is much weaker because the restrictions against switching banks eliminates the expansionary extensive-margin effect.

V.2. **Reducing national bank RR.** Figures 4 displays the impulse responses to a 1% negative RR shock on national banks ($\epsilon^n_{\tau,t} = -0.01$). In the case with no switching costs ($\gamma = 0$), cutting τ_n has two opposite effects: At the intensive margin, it lowers national banks' required return on lending falls, which and encourages increased firms borrowing from national banks to take on more leverage. At the extensive margin, firms shift from local banks to national banks. This lowers the average firm leverage ratio as local banks' superior

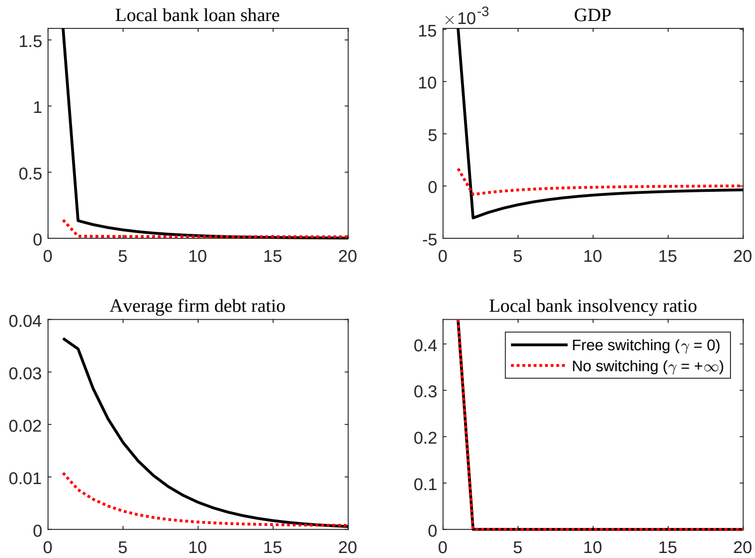

FIGURE 3. Impulse responses of a 1% negative RR shock on local banks ($\epsilon^{l}_{\tau,t} = -0.01$). Black solid lines: no switching costs ($\gamma = 0$); red dotted lines: infinite switching costs ($\gamma = +\infty$). The horizontal axes show the quarters after the impact period of the shock. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for local bank insolvency ratio. The units on the vertical axes are percent deviations from the steady state levels for other variables.

monitoring technologies induce them to accept riskier borrowers. Under our calibration, the extensive-margin effect dominates and cutting τ_n leads to a fall in total output.

In the case with infinite switching costs ($\gamma = +\infty$), firms do not switch between banks, so the extensive-margin effect no longer operates. Cutting τ_n raises national bank lending, reducing firm funding costs and raising output.

VI. Business cycle analysis

In this section, we consider the dynamic implications of pursued RR policy in China in the wake of adverse technology shocks. We characterize China RR policy in terms of two alternative feedback rules which the central bank follows in response to deviations of the real GDP from its trend. One rule is assumed to prevail under normal conditions, and the other is adopted in response to deep downturns. We compare these dynamics to a benchmark regime where RR of both types of banks are kept constant at their steady state levels over the course of the cycle.

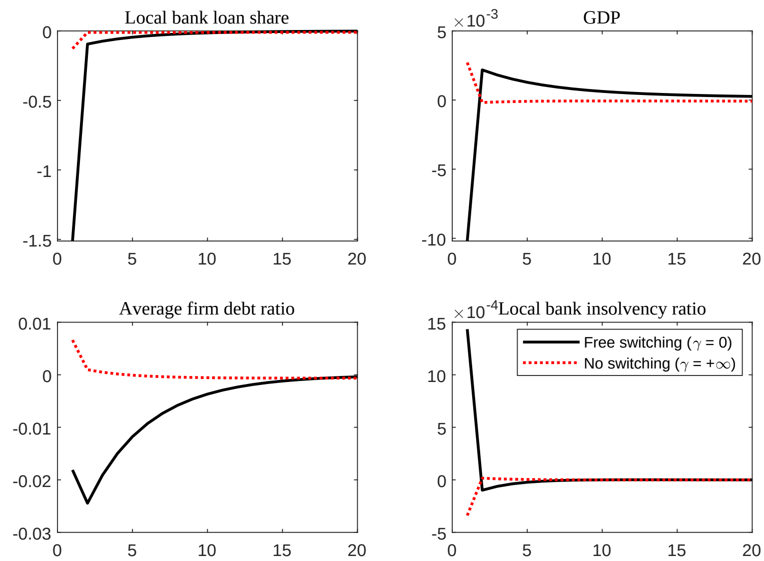

FIGURE 4. Impulse responses of a 1% negative RR shock on national banks ($\epsilon^n_{\tau,t} = -0.01$). Black solid lines: no switching costs ($\gamma = 0$); red dotted lines: infinite switching costs ($\gamma = +\infty$). The horizontal axes show the quarters after the impact period of the shock. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for local bank insolvency ratio. The units on the vertical axes are percent deviations from the steady state levels for other variables.

Under our calibration, firms borrow from both types of banks and are indifferent between the two types of banks in the initial steady state. As is implied by (A1), they switch across banks only when the economy is hit by a sufficiently large shock that the improvement in the their return to equity of switching from one bank to another exceeds the switching cost. This implies that our model contains occasionally binding constraints.[7]

VI.1. **RR rules.** The central bank adjusts the required reserve ratio ($\tau_{n,t}$ or $\tau_{l,t}$) to respond to deviations of real GDP from trend.

$$\tau_{l,t} = \bar{\tau}_l + \psi_{ly} \ln\left(\tilde{GDP}_t\right) \tag{46}$$

$$\tau_{n,t} = \bar{\tau}_n + \psi_{ny} \ln\left(\tilde{GDP}_t\right) \tag{47}$$

[7]We solve the model using a popular model solution toolbox called OccBin developed by Guerrieri and Iacoviello (2015). The toolbox adapts a first-order perturbation approach and applies it in a piecewise fashion to solve dynamic models with occasionally binding constraints.

where the parameters ψ_{ly} and ψ_{ny} measure the responsiveness of the require reserve ratios to the output gap.

We first consider a symmetric RR rule which characterizes PBOC policy under normal conditions, under which the reaction coefficients satisy $\psi_{ly} = \psi_{ny} = 1$. We estimate the value of the reaction coefficient by regressing the RRs on the real GDP gap and the CPI inflation rate using Chinese quarterly data from 2000 to 2020.

Our second RR rule is asymmetric, under which the RR reaction coefficients $\psi_{ly} = 2$ and $\psi_{ny} = 0$, and reflects pursued PBOC policy in the wake of deep adverse shocks. Under this rule, the central bank aggressively cuts RRs on local banks in response to downturns but only modestly adjusts RRs on national banks. This fits the pattern of pursued policy during the recent coronavirus pandemic.[8]

VI.2. **Impulse responses.**

VI.2.1. *Large shocks versus small shocks.* To begin with, we explore the macro implications of technology shocks with different shock sizes in a benchmark regime where RR of both types of banks are kept constant at their steady state levels. Figure 5 compares the impulse responses of a relatively small negative technology shock $\epsilon_{at} = -0.01$ and a relatively large negative technology shock $\epsilon_{at} = -0.05$ in the benchmark regime.

We first focus on a relatively small negative technology shock $\epsilon_{at} = -0.01$, whose responses are shown in black solid lines. The negative technology shock reduces firms' return to investment, imposing upward pressure on firm default possibilities and credit spreads at existing lending levels. In response to higher spreads and reduced profitability, firms respond by reducing their leverage ratio. This leads to reduced returns on equity.

Firms that borrow from local banks are more negatively affected than those that borrow from national banks. Local banks, due to their monitoring advantages, have higher steady state leverage and default probabilities. This leaves local bank terms more sensitive to adverse shocks than national banks. However, under the small technology shock the switching cost is too high, precluding firms borrowing from local banks from switching to national banks. Alternatively, consider a relatively large negative technology shock $\epsilon_{at} = -0.05$, whose responses are shown in red dotted lines. the negative technology shock reduces all firms' return to equity, although more acutely for firms borrowing from local banks. In this case, the improvement in returns to equity from switching to national banks are large enough to cover the switching cost for some local bank borrowers. As a result, while total lending

[8] As shown in Figure 1, the PBOC dropped RR for both large banks as well as medium and small banks during the 2008 global financial crisis. However, it dropped those for medium and small banks far more aggressively than it did for large banks, in line with the asymmetry pursued during the pandemic.

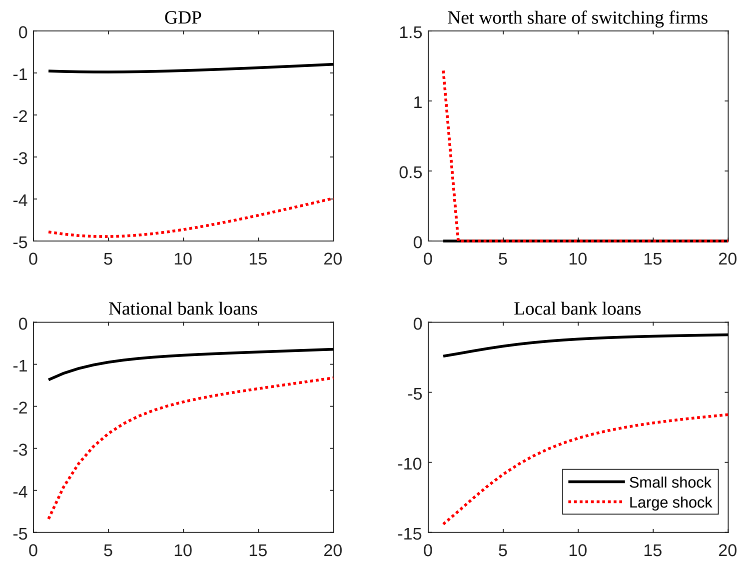

FIGURE 5. Impulse responses to a small negative technology shock ($\epsilon_{at} = -0.01$, black solid lines) and to a large negative technology shock ($\epsilon_{at} = -0.05$, red dotted lines). The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for the variable "Net worth share of switching firms", which refers to the ratio of the net worth of firms that switch from local banks to national banks to the net worth of all firms. The units on the vertical axes are percent deviations from the steady state levels for other variables.

falls, national bank lending rises. The shift to national banks also lowers the average leverage ratio, further reducing total output.

An important take-away from Figure 5 is that local banks' credit supply are more cyclically sensitive than national banks. Furthermore, this extra sensitivity is larger in times of large shocks, attributed to firm switching across the two types of banks. These results are supported by the empirical evidence using Chinese bank-level data, which we will show later in Section VII.

VI.2.2. *Symmetric versus asymmetric RR rule under small shocks.* Figure 6 displays the impulse responses to a relatively small negative technology shock $\epsilon_{at} = -0.01$ under alternative policy rules. With no switching taking place, the decline in aggregate TFP leads to a fall in real GDP. In this case, the symmetric RR policy and the asymmetric RR policy are almost equally effective in stabilizing the output. In particular, the RR cut on both types of banks under the symmetric rule reduces the funding costs of both types of banks and mitigates the fall in real GDP by raising credit supply in both banking sectors. In contrast,

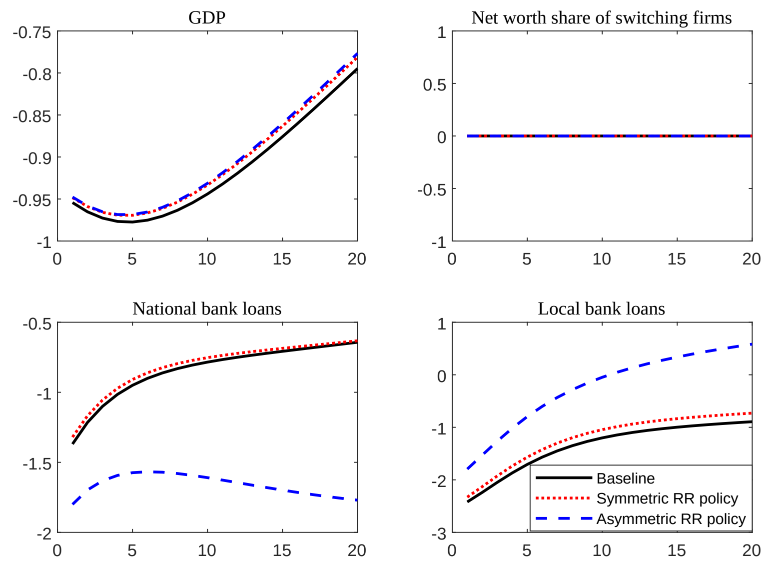

FIGURE 6. Impulse responses to a small negative technology shock ($\epsilon_{at} = -0.01$) under alternative policy rules. Benchmark rule: black solid lines; symmetric RR rule: blue dashed lines; assymmetric rule: red dotted lines. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for the variable "Net worth share of switching firms", which refers to the ratio of the net worth of firms that switch from local banks to national banks to the net worth of all firms. The units on the vertical axes are percent deviations from the steady state levels for other variables.

the asymmetric cut that only reduces RR on local banks stimulates the credit supply by local banks but tightens the credit supply by national banks.

VI.2.3. *Symmetric versus asymmetric RR rule under large shocks.* Figure 7 displays the impulse responses to a large negative technology shock $\epsilon_{at} = -0.05$ under alternative policy rules. Given the large shock, the RR cut on both types of banks helps to reduce all banks' funding costs and mitigates the fall in the real GDP. However, the asymmetric cut stabilizes the real GDP better than cutting RRs symmetrically across bank types. This is because the asymmetric RR cut lowers the local bank lending rate relative to that of national banks, preventing switching to national banks. By comparison, while the symmetric cut stimulates both types of bank lending, it does not raise the total credit as much because firms switch to national banks.

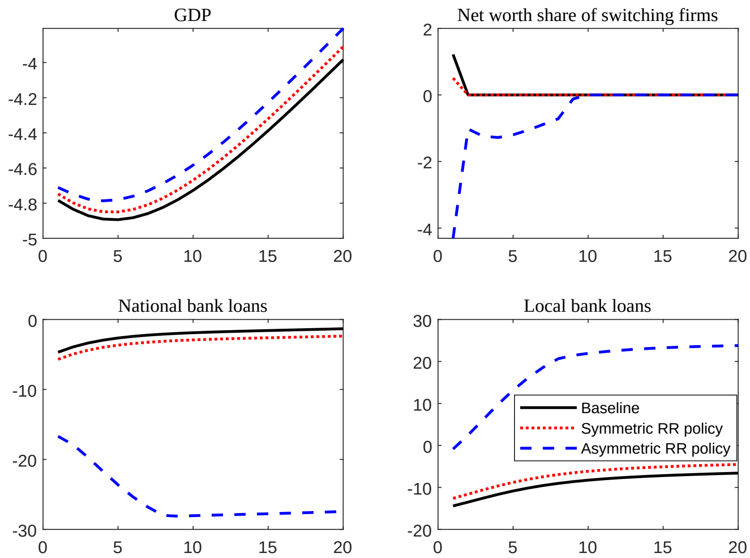

FIGURE 7. Impulse responses to a large negative technology shock ($\epsilon_{at} = -0.05$) under alternative policy rules. Benchmark rule: black solid lines; symmetric RR rule: blue dashed lines; assymmetric rule: red dotted lines. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for the variable "Net worth share of switching firms", which refers to the ratio of the net worth of firms that switch from local banks to national banks to the net worth of all firms. The units on the vertical axes are percent deviations from the steady state levels for other variables.

VI.3. **Optimal asymmetric RR adjustments.** In this section, we consider a variety of technology shock sizes and study the optimal rule and the relative performance of the asymmetric RR policy under various shock sizes. In particular, based on Chinese quarterly data on RR adjustments and real GDP, we restrict the average of the two RR reaction coefficients ψ_{ny} in (47) and ψ_{ly} in (46) to be equal to 1. Given this restriction ($\frac{\psi_{ny}+\psi_{ly}}{2} = 1$), the government chooses the two reaction coefficients ψ_{ny} and ψ_{ly} to minimize the loss function as follows,

$$L = \mathrm{E}\left[(\tilde{C}_t)^2 + \Psi_h \eta \bar{H}^{1+\eta}(\tilde{H}_t)^2\right] \tag{48}$$

where $\tilde{C}_t$ denotes the deviation of consumption from trend; $\bar{H}$ and $\tilde{H}_t$, respectively, denotes the steady-state value of labor hours and its deviation from the steady state. The above loss function is derived from the second-order approximation of the household's welfare except that the planner does not value bank deposit balances.[9]

To solve for the optimal values of ψ_{ly} and ψ_{ny}, we perform a grid search within a reasonable range $\psi_{ly} - \psi_{ny} \in [-2, 2]$. Note that the government implements symmetric RR policies when $\psi_{ly} = \psi_{ny} = 1$.

Figure 8 considers the impact of alternative asymmetric RR policies under a variety of technology shock sizes. The figure demonstrates a tradeoff between macro stability and bank insolvency costs when the government adopts asymmetric RR policies: an increase in the difference in RR reaction coefficient between local banks and national banks $\psi_{ly} - \psi_{ny}$ helps stabilizes the GDP but makes bankruptcies in local banks more volatile. This is because adverse technology shocks reduce firm investment returns and returns on local bank lending, raising the incidence of local bank insolvency. Under these circumstances, if the government cuts the RR on local banks to stimulate the output for macro stabilization, the fraction of insolvent local banks increases further, raising financial instability.

It is also notable that, the larger the shock, the more efficient is raising $\psi_{ly} - \psi_{ny}$ in stabilizing the economy. This reason is demonstrated in our impulse responses, where the more aggressive cut of RR on local banks relative to national banks helps reduce the amount of costly switching between banks or even reverse the switching during severe economic downturns.

Figure 9 considers a variety of technology shock sizes and shows the optimal policy rule and its performance under various shock sizes. We found that, when the shock size is sufficiently small ($\sigma_a \leq 0.02$), the RR on local banks responds to the output gap less aggressively than the RR on national banks. This is because, given adverse technology shocks, the RR cut on local banks raises local bank insolvency. However, as national banks are less risk tolerant, the RR cut on national banks stabilizes with lower increases in financial stability.

However, when the shock size is large enough ($\sigma_a \geq 0.03$), the RR on local banks responds to the output gap more aggressively than the RR on national banks. This is because, under large shocks, firms begin to switch between banks and the extensive-margin effect from bank switching will exaggerate the output fluctuations. In this case, RR adjustments on local banks could help reduce the bank switching behavior and therefore stabilize the output more efficiently relative to the case with small shocks and no bank switching by firms.

[9]Including national banks' deposits in the loss function would imply that the social planner treats the two banking sectors differently and tends to stabilize the national banking sector, which seemed to be an unappealing feature in the welfare analysis.

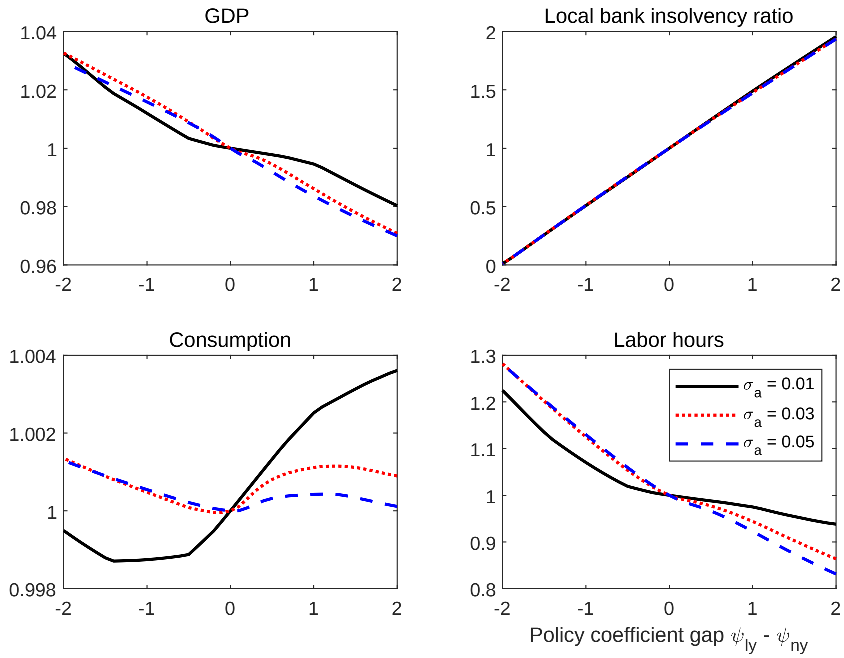

FIGURE 8. Performance of various asymmetric RR policies under technology shocks. The horizontal axes show the difference in RR reaction coefficient between local banks and national banks $\psi_{ly} - \psi_{ny}$. The vertical axes show the volatility of the corresponding variable under the alternative policy regime scaled by the volatility of the variable under the symmetric RR policy where $\psi_{ly} = \psi_{ny} = 1$.

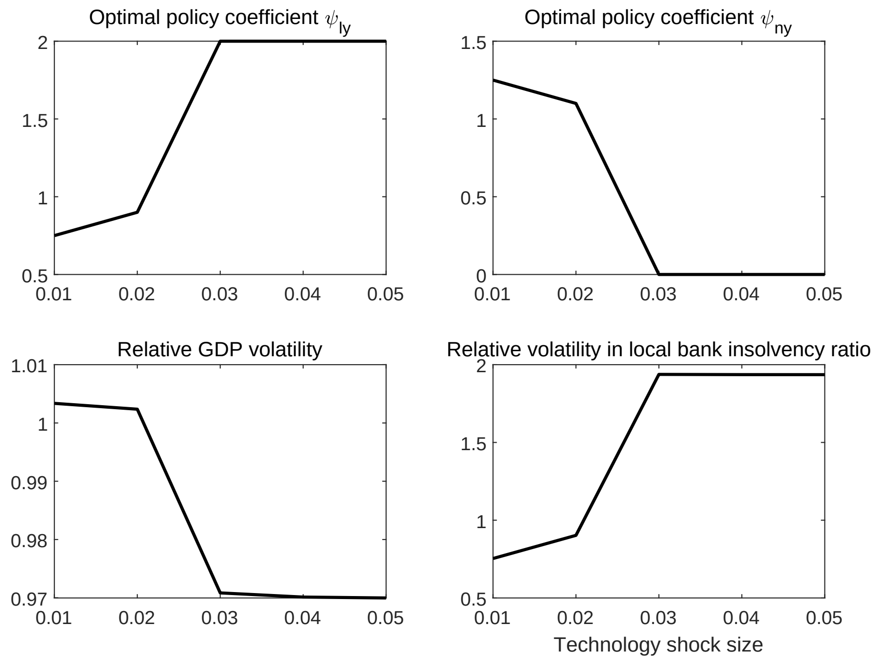

FIGURE 9. Optimal asymmetric RR policy under technology shocks. The horizontal axes show the size of the technology shock σ_a. The upper left panel and the upper right panel, respectively, show the optimal values of the two reaction coefficients ψ_{ly} for local banks and ψ_{ny} for national banks. The lower left panel and the lower right panel, respectively, shows the ratio of the volatility in output gap $\sqrt{\mathrm{E}[(G\tilde{D}P_t)^2]}$ and the volatility in local bank bankruptcy ratio $\sqrt{\mathrm{E}\left[(F(\bar{\epsilon}_{l,t}))^2\right]}$ under the optimal asymmetric RR policy to its counterpart under the symmetric RR policy where $\psi_{ly} = \psi_{ny} = 1$.

VII. Empirical evidence

In our model, small banks, due to their monitoring advantages, allow for higher firm leverage and default probabilities in the steady state than large banks. As a consequence, small bank lending responds more to business cycle fluctuations than large banks. Furthermore, sufficiently large shocks may disrupt banking relationships and increase the discrepancy between small and large bank lending volatility, justifying the use of asymmetric RR for the two types of banks. In this section, we show that these disparities in large and small bank lending sensitivities to business cycle movements are consistent with empirical evidence for banks in China.

VII.1. **Methodology.** China's commercial banking sector consists of the five largest state-owned banks (commonly known as the "Big Five"), twelve joint-stock banks, and a large number of medium-sized urban banks and small-sized rural banks. Differences in bank size are primarily attributable to the differences in operating areas: While the Big Five have branches nationwide, other commercial banks usually concentrate their lending in a specific area. In particular, rural banks are restricted to focus their lending activity within certain county-level towns or villages. In contrast, urban banks are less focused as they are allowed to operate within a province or a prefectural-level city, which usually includes a main central urban area and its surrounding rural areas. Finally, joint-stock banks have national operating licenses and are allowed to operate nationally. However, most joint-stock banks are evolved from urban banks and usually concentrate their lending in one area comparable in size to those of urban banks.

As discussed above, China banks also are subject to different policy treatment by group, including PBoC discrimination across banks by size in RR. To identify the implications of these policy treatment differences, we consider a sample of banks subject to different local economic shocks. Specifically, we focus on medium-sized and small-sized commercial banks, dropping the large-sized commercial banks (the Big Five) from our sample because their loan portfolios are diversified nationally. We compare how these two groups of banks respond differently to regional economic shocks using the following empirical specification:

$$\Delta L_{i,t} = c + \beta \Delta Y_{j(i),t} \times SM_i + \beta_x X_{i,t-1} + \theta_t + Z_i + P_j \times \theta_t + SM_i \times \theta_t + \epsilon_{i,t} \tag{49}$$

where the dependent variable $\Delta L_{i,t}$ denotes the growth rate in bank i's loan from year $t-1$ to year t. $\Delta Y_{j(i),t}$ denotes the real GDP growth in province $j(i)$ in year t, where $j(i)$ denotes the province where bank i's headquarter locates. SM_i is a dummy variable that equals one if bank i is a rural bank, and zero if bank i is an urban bank or a joint-stock bank. $X_{i,t-1}$ denotes a battery of control variables to control for bank-specific characteristics that may influence bank lending over our sample. This set of control variables use lagged values and includes the deposit to asset ratio $D/A_{i,t-1}$, the equity to asset ratio $E/A_{i,t-1}$, the non-performing loan ratio $NPL_{i,t-1}$, the interest income and fees to asset ratio $INT/A_{i,t-1}$, and the loan to asset ratio $L/A_{i,t-1}$.[10] θ_t, Z_i and P_j represents year, bank and province dummies, respectively. We include province-year dummies $P_j \times \theta_t$ to control for potential endogenous co-movements between bank loan and real GDP at the province level. We also include interaction between small-bank dummies SM_i and the year dummies θ_t to control for the impacts from differential policy treatments based on bank size at the national level. Note that we do not include province dummies P_j or small-bank dummies SM_i in the above specification because they are collinear with the bank dummies Z_i in our sample.

In our baseline specification (49), we use province-specific real GDP growth $\Delta Y_{j(i),t}$ to capture the variations in local economic conditions that affect the market equilibrium of bank loans. The dummy variable SM_j is used to distinguish small-sized banks ($SM_i = 1$) from medium-sized banks ($SM_i = 0$). The coefficient of interest is β, the coefficient on the interaction between these two variables. In particular, β captures the additional sensitivity of small banks' loan growth to changes in local real GDP growth and should be positive based on our model.

VII.2. **Data.** We obtain Chinese bank-level data and province-level data from China Stock Market & Accounting Research Database (CSMAR). Our bank-level dataset is an unbalanced panel of 320 small-sized commercial banks and 142 medium-sized commercial banks at the annual frequency over a sample period from 2008 to 2021. The number of banks in our sample starts from 92 in 2008, reaches 448 in 2019 and ends with 350 in 2021, with bank entry and exit in each year. Table 2 displays the summary statistics of our bank-level sample, which we have winsorized at the 1% level to ensure that our results are not driven by outliers. We also display the summary statistics for small-sized commercial banks and medium-sized commercial banks separately. Table 2 shows that means of banking characteristics measures for the two types of banks in our sample are comparable, although standard deviations of characteristics are generally larger for the small bank group.

Our province-level data provides the province-specific real GDP growth $\Delta Y_{j,t}$ used in our regression and is a balanced panel of 29 province-level regions that cover the headquarter location of all the banks in our bank-level sample. The province-level data is also winsorized at the 1% level.

Table 3 shows how our bank-level sample is distributed across location regions and bank size types. We can see that our bank-level sample displays significant heterogeneity in

[10] Here, "assets" refers to book value of total assets.

Table 2. Summary Statistics

	Full sample			Small-sized banks ($SM_i = 1$)			medium-sized banks ($SM_i = 0$)		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
$\Delta L_{i,t}$	3,685	0.18	0.12	2,155	0.15	0.11	1,530	0.22	0.13
$D/A_{i,t}$	2,893	0.78	0.98	1,442	0.86	1.38	1,451	0.71	0.12
$E/A_{i,t}$	2,903	0.08	0.03	1,451	0.09	0.03	1,452	0.07	0.02
$NPL_{i,t}$	3,668	1.89	1.32	2,145	2.20	1.47	1,523	1.45	0.90
$INT/A_{i,t}$	2,877	0.05	0.01	1,430	0.05	0.01	1,447	0.05	0.02
$L/A_{i,t}$	2,894	0.52	0.58	1,443	0.59	0.81	1,451	0.45	0.11
$\Delta Y_{j(i),t}$	4,458	0.08	0.03	2,771	0.08	0.02	1,687	0.08	0.03

Note: This table displays summary statistics of our bank-level sample used in the baseline regression. It also displays summary statistics for small-sized commercial banks ($SM_i = 1$) and for medium-sized commercial banks ($SM_i = 0$). The bank-level variables include bank loan growth $\Delta L_{i,t}$, deposit to asset ratio $D/A_{i,t}$, equity to asset ratio $E/A_{i,t}$, nonperforming loan ratio $NPL_{i,t}$, interest income and fees to asset ratio $INT/A_{i,t}$, loan to asset ratio $L/A_{i,t}$. N is the number of non-missing observations in the sample for each variable.
Source: China Stock Market & Accounting Research Database (CSMAR).

location regions. In particular, even the region that is located by most banks (69 banks) and has the largest number of bank-year observations (715), the Fujian province, only accounts for around 15% of 462 banks and 715 bank-year observations in the full bank-level sample.

VII.3. **Baseline estimates.** We report the estimation results under our baseline specification (49) using the full sample in Table 4 Column 1. The estimated value of β is positive and statistically significant at the 5% level, consistent with our model's prediction. The estimated value of β is also economically significant. Our point estimate indicates that a one percentage point increase in the real GDP growth would increase the loan growth rate of an average small-sized commercial bank relative to a medium-sized commercial bank by 1.212 percentage point.

TABLE 3. Sample distribution by location region and bank size type

	Number of banks			Number of bank-year observations		
Region name	$SM_i = 1$	$SM_i = 0$	Total	$SM_i = 1$	$SM_i = 0$	Total
Fujian	64	5	69	649	63	712
Zhejiang	33	13	46	352	173	525
Jiangsu	38	4	42	397	51	448
Anhui	45	1	46	425	14	439
Guangdong	24	8	32	205	100	305
Sichuan	19	14	33	120	157	277
Shandong	5	15	20	35	201	236
Jiangxi	20	3	23	147	42	189
Liaoning	6	12	18	41	136	177
Henan	12	12	24	58	83	141
Hebei	8	10	18	24	108	132
Beijing	2	5	7	22	70	92
Hunan	11	2	13	54	26	80
Shanxi	4	6	10	16	60	76
Inner Mongolia	7	3	10	31	35	66
Hubei	4	2	6	37	25	62
Guangxi	2	3	5	18	42	60
Chongqing	3	2	5	29	27	56
Shaanxi	3	2	5	21	26	47
Shanghai	1	2	3	14	28	42
Tianjin	1	2	3	12	28	40
Ningxia	1	2	3	13	26	39
Guizhou	2	2	4	17	21	38
Yunnan	0	3	3	0	38	38
Jilin	2	1	3	21	13	34
Xinjiang	2	3	5	2	32	34
Heilongjiang	0	2	2	0	26	26
Qinghai	1	1	2	11	13	24
Gansu	0	2	2	0	23	23
Total	320	142	462	2,771	1,687	4,458

Note: Each row of this table shows the number of banks and the number of bank-year observations for a subsample of banks whose headquarter locates in a given province-level region. The table also displays the number of banks and the number of bank-year observations for small-sized commercial banks ($SM_i = 1$) and for medium-sized commercial banks ($SM_i = 0$).

Table 4. Regression results.

Sample	(1) Full	$D = 0.04$		$D = 0.03$		$D = 0.05$	
		(2) Small shock	(3) Large shock	(4) Small shock	(5) Large shock	(6) Small shock	(7) Large shock
$\Delta Y_{j(i),t} \times SM_i$	1.212**	1.318	2.995**	1.196	3.404***	1.333*	10.183***
	(0.584)	(0.830)	(1.416)	(0.989)	(1.223)	(0.798)	(2.113)
$D/A_{i,t-1}$	0.395***	0.398***	0.162	0.396***	0.173*	0.396***	0.304***
	(0.049)	(0.060)	(0.112)	(0.064)	(0.105)	(0.057)	(0.106)
$E/A_{i,t-1}$	1.070***	1.104***	1.551***	1.092***	1.321***	1.087***	2.619***
	(0.189)	(0.209)	(0.546)	(0.216)	(0.411)	(0.201)	(0.661)
$NPL_{i,t-1}$	−0.007**	−0.007**	−0.022	−0.007**	−0.004	−0.007**	−0.016
	(0.003)	(0.003)	(0.024)	(0.004)	(0.007)	(0.003)	(0.029)
$INT/A_{i,t-1}$	−0.503***	−0.764	−0.668***	−1.011*	−0.528***	−0.579***	8.865***
	(0.188)	(0.518)	(0.101)	(0.540)	(0.179)	(0.185)	(1.901)
$L/A_{i,t-1}$	−0.665***	−0.668***	−0.559***	−0.663***	−0.663***	−0.666***	−0.415**
	(0.085)	(0.103)	(0.112)	(0.110)	(0.112)	(0.098)	(0.189)
$Constant$	0.193***	0.195***	0.579*	0.211***	0.247**	0.190***	−0.373
	(0.042)	(0.049)	(0.303)	(0.049)	(0.119)	(0.045)	(0.238)
Sample size	2706	2291	415	2103	603	2412	294
Adjusted R-square	0.37	0.36	0.72	0.33	0.58	0.37	0.78

Note: The dependent variable is $\Delta L_{i,t}$ in all specifications. Bank dummies Z_i, year dummies θ_t, province-year dummies $P_j \times \theta_t$, small-bank-year dummies $SM_i \times \theta_t$ are included in all specifications. Column (1) reports the estimates using the full sample. Column (2)-(7) reports the estimates for subsample of small shocks or large shocks. A bank-year observation is classified in the large (small) shock subsample if the bank locates in the province whose real GDP growth in current year deviates from its historical average by more (less) than a threshold level D. Standard error clustered at the bank level are shown in parentheses. Statistical significance levels are indicated by the asterisks: $^{***}: p < 0.01$, $^{**}: p < 0.05$, and $^{*}: p < 0.10$.

VII.4. **Subsample estimates.** Our model also predicts that the disparity between large and small bank sensitivity is larger in times of sufficiently large shocks. To show this, we estimate our baseline specification (49) in two sub-samples: a "large shock" sub-sample and a "small shock" sub-sample. The classification is based on how much the province-specific real GDP growth $\Delta Y_{j,t}$ deviates from its historical average $\Delta Y_j \equiv \frac{1}{15}\sum_{t=2007}^{2021} \Delta Y_{j,t}$. In particular, we classify a bank i in a given province $j(i)$ as experiencing large shocks in year t if the province-specific real GDP growth deviates from its historical average by more than a threshold level D (i.e. $|\Delta Y_{j,t} - \Delta Y_j| > D$), and in the "small shock" sub-sample if otherwise (i.e. $|\Delta Y_{j,t} - \Delta Y_j| \leq D$). We set the threshold level D to minimize out-of-sample mean squared error based on the sub-sample estimates.[11] In this way, we obtains $D = 0.04$ as a benchmark, which is around 1.3 times the standard deviation of China's national real GDP growth over our sample period. To check the robustness of our results, we also consider two alternative thresholds for large shocks, $D = 0.03$ and $D = 0.05$.

Figure 10 shows the fraction of banks that are classified as experiencing a "large shock" in our sample. Most of the "large shock" observations occur during the 2007 global financial crisis and the recent Covid pandemic in 2020, precisely the periods in which the PBoC implements targeted RR adjustments based on bank size.

We report the estimation results under our baseline specification (49) for the two subsamples in Table 4 Column 2 and 3. The estimated value of β is not significant from zero in the "small shock" sample but becomes significantly positive in the "large shock" sample. The value of β estimated in the "large shock" sample is around 2.5 times as large as the full-sample estimate shown in Column 1. These results suggest that, compared with medium-sized commerical banks, small-sized commerical banks' lending activities are particularly sensitive to local economic growth in times of large shocks.

The empirical evidence is robust to alternative definitions of large shocks. Table 4 Column 4-7 reports the estimation results when we change the threshold level to $D = 0.03$ or $D = 0.05$. The value of β estimated in the "large shock" sample is still significantly larger than the "small shock" estimate. Notably, when we tighten the criterion to identify large shocks by raising the threshold level to $D = 0.05$, the value of β estimated for the "large shock" sample (shown in Column 7) become almost 10 times as large as the full-sample estimate (shown in Column 1).

VII.5. **Robustness.** We have conducted some robustness checks, with results presented in Appendix D.

[11] Appendix C provides details on the calculation of the out-of-sample mean squared error and reports its values for various threshold levels of D.

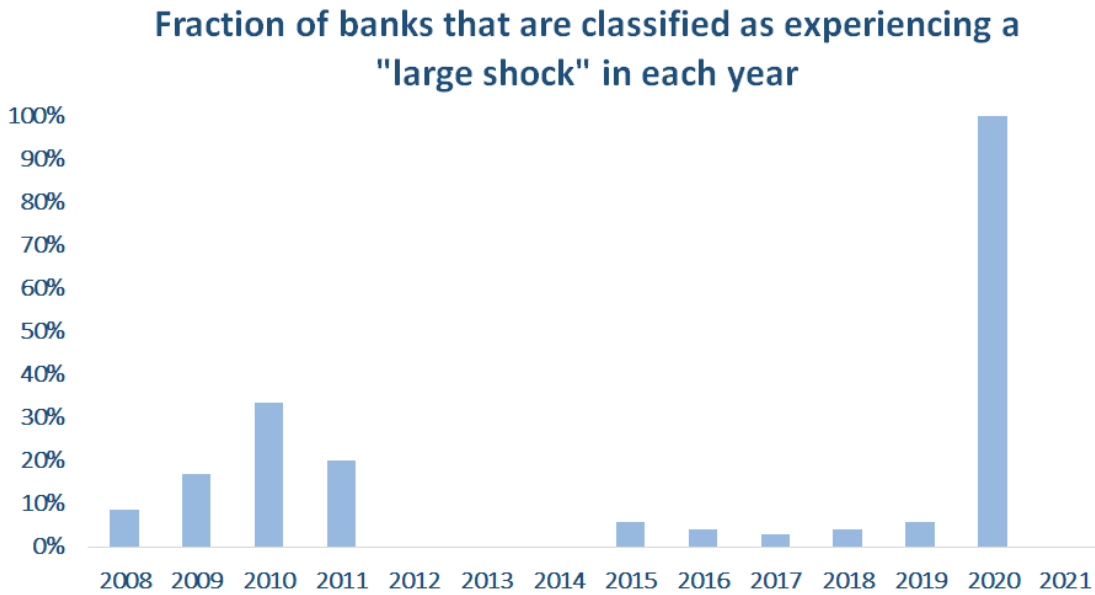

Figure 10. Fraction of banks that are classified as experiencing a ”large shock” in each year over the sample period 2008 to 2021.

Note: A bank-year observation is classified in the large (small) shock subsample if the bank locates in the province whose real GDP growth in current year deviates from its historical average by more (less) than a threshold level $D = 0.04$.

VII.5.1. *Unwinsorized data.* We examine the robustness of our results to the use of unwinsorized data, which is shown in Table D1. We obtain qualitatively similar results as those in the baseline when we do not winsorize the data. Notably, the estimate value of β for the ”large shock” sample is extremely large (104.5) when a relatively high threshold level ($D = 0.05$) is used. This result further verifies our model's mechanism where, in times of sufficiently large shocks, costly disruption of banking relationships could dramatically raise the extra business cycle sensitivity of small banks, thus generating outliers in the data.

VII.5.2. *Alternative standard error.* We re-estimate our baseline specification with standard errors clustered at the province level instead of the firm level. Table D2 shows that such variation does not change the statistical significance of our estimates.

VIII. Conclusion

We have studied the effectiveness of targeted changes in reserve requirement policy as a macroeconomic stabilization tool, a policy that has been implemented by China during the global financial crisis and the COVID-19 pandemic. We present a theoretical model in which firms can borrow from either local or national banks. The two types of banks coexist because local banks have access to superior monitoring technologies whereas national banks provide superior liquidity services and thus face lower funding costs. Borrowers can switch bank types by paying a fixed cost. Thus, costly bank switching would occur only in the presence of sufficiently large shocks.

Using our theoretical framework, we show that targeted RR policy helps stabilize macroeconomic fluctuations, especially when the economy is buffeted by large shocks. Under optimal RR rules, the central bank cuts RR more aggressively for local banks than for national banks in response to a large decline in output gap. By following such targeted RR rules, monetary policy helps mitigate costly bank switching in deep recessions and therefore stabilizing macroeconomic fluctuations and improving welfare.

The model mechanism and the main predictions are in line with empirical evidence. Consistent with theory, bank-level evidence suggests that lending growth of small banks is on average more sensitive to local shocks than medium-sized banks. Furthermore, when the shocks are large, lending of small banks responds significantly more than that of medium-sized banks. These findings are robust and lend support to the model mechanism.

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Appendix A. Changes in aggregate net worth subsequent to switching banks

Given firms' optimal choices of the bank type in Eq. (29), the beginning-of-period net worth is given by

$$\begin{cases} N_{l,t} \in (\bar{N}_{l,t-1}, \bar{N}_{t-1}), N_{n,t} \in (0, \bar{N}_{n,t-1}), & \text{if} \quad \bar{V}_{l,t}ROE_{l,t} - \bar{V}_{n,t}ROE_{n,t} = \gamma \bar{V}_{l,t}, \\ N_{l,t} = \bar{N}_{l,t-1}, N_{n,t} = \bar{N}_{n,t-1}, & \text{if} \quad -\gamma \bar{V}_{n,t} < \bar{V}_{l,t}ROE_{l,t} - \bar{V}_{n,t}ROE_{n,t} < \gamma \bar{V}_{l,t}, \\ N_{l,t} \in (0, \bar{N}_{l,t-1}), N_{n,t} \in (\bar{N}_{n,t-1}, \bar{N}_{t-1}), & \text{if} \quad \bar{V}_{l,t}ROE_{l,t} - \bar{V}_{n,t}ROE_{n,t} = -\gamma \bar{V}_{n,t}. \end{cases} \tag{A1}$$

Eq. (A1) identifies three possible ranges for changes in aggregate net worth subsequent to switching banks. In the first range, the benefit of switching to a local bank sufficiently exceeds the benefit of borrowing from a national bank so that some of previous national-bank borrowers switch to local banks until the benefit of switching from a national bank to a local banks is driven down to be equal to the cost of switching, i.e. $\bar{V}_{l,t}ROE_{l,t} - \bar{V}_{n,t}ROE_{n,t} = \gamma \bar{V}_{l,t}$. Such switching behavior raises the aggregate net worth of local-bank borrowers from $\bar{N}_{l,t-1}$ by the end of previous period $t-1$ to $N_{l,t}$ at the beginning of period t, and reduces the aggregate net worth of national-bank borrowers from $\bar{N}_{n,t-1}$ by the end of previous period $t-1$ to $N_{n,t}$ at the beginning of period t. In this case, $N_{l,t} - \bar{N}_{l,t-1} \equiv \bar{N}_{n,t-1} - N_{n,t} > 0$ measures the aggregate net worth of firms that switch from a national bank to a local bank.

In the second range, borrowers do not switch banks because the benefit of doing so is less than the switching cost. As a consequence, the aggregate net worth of each type of borrowers do not change, i.e. $N_{l,t} = \bar{N}_{l,t-1}, N_{n,t} = \bar{N}_{n,t-1}$.

The third range is mirror-image of the first, as the benefit of switching to a national bank sufficiently exceeds the benefit of borrowing from a local bank so that previous local-bank borrowers switch to national banks until the benefit of switching is again driven down to its cost, i.e. $\bar{V}_{n,t}ROE_{n,t} - \bar{V}_{l,t}ROE_{l,t} = \gamma \bar{V}_{n,t}$. In this case, the aggregate net worth of firms that switch from a local bank to a national bank is measured by $N_{n,t} - \bar{N}_{n,t-1} \equiv \bar{N}_{l,t-1} - N_{l,t} > 0$.

Eq. (A1) gives the optimal choice of bank type in the interior solution where firms borrow from both types of banks, which will be the case under our calibration. It is also notable that, with extreme calibrated values, the gap in the overall return to equity between the two types of banks could be large enough so that all firms choose the same bank type in a corner solution:

$$\begin{cases} N_{l,t} = \bar{N}_{t-1}, N_{n,t} = 0, & \text{if} \quad \bar{V}_{l,t}ROE_{l,t} - \bar{V}_{n,t}ROE_{n,t} > \gamma \bar{V}_{l,t}, \\ N_{l,t} = 0, N_{n,t} = \bar{N}_{t-1}, & \text{if} \quad \bar{V}_{l,t}ROE_{l,t} - \bar{V}_{n,t}ROE_{n,t} < -\gamma \bar{V}_{n,t}. \end{cases} \tag{A2}$$

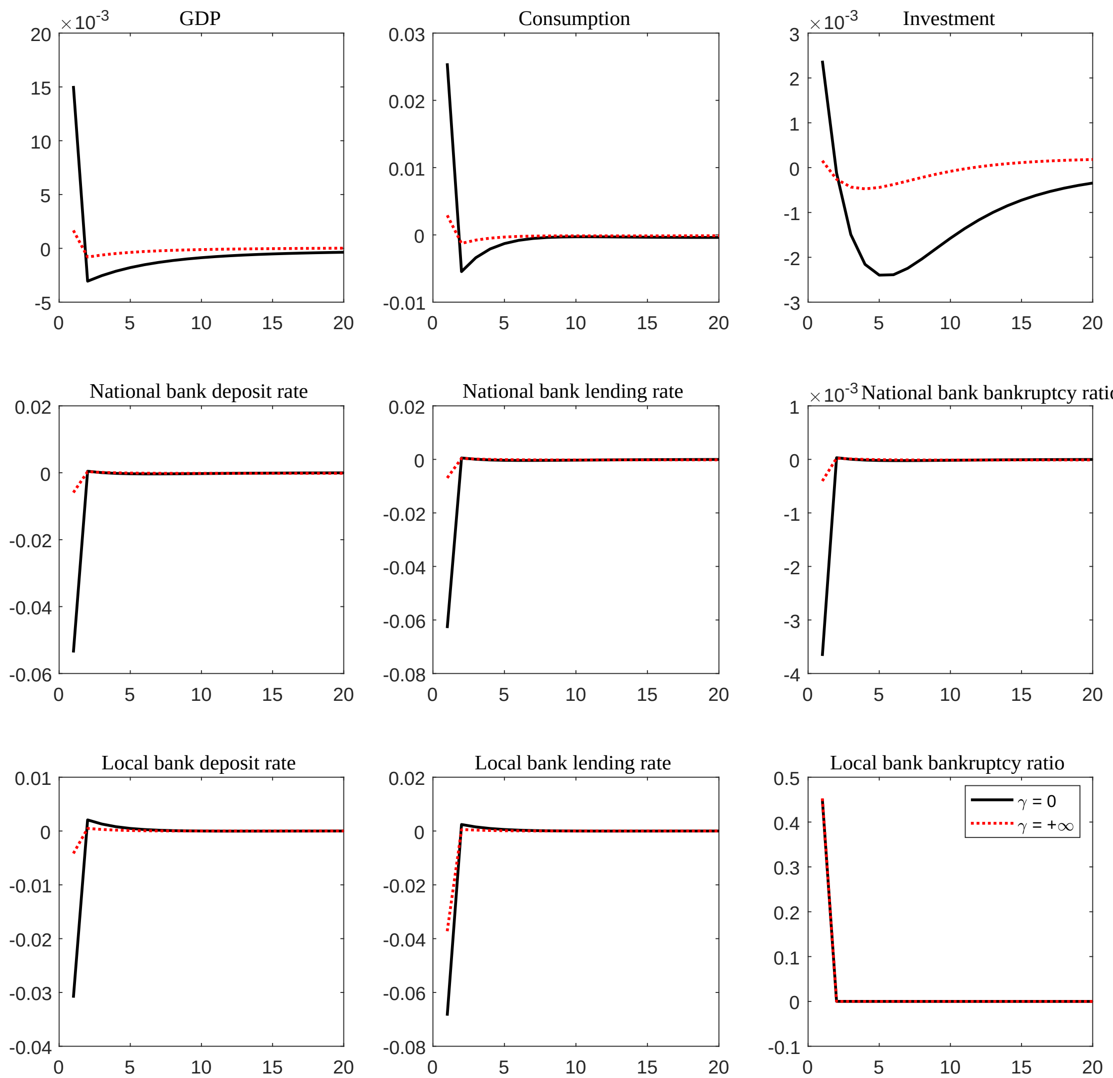

FIGURE B1. Impulse responses of a 1% negative RR shock on local banks ($\epsilon^l_{\tau,t} = -0.01$) for macroeconomic variables. Black solid lines: no switching costs ($\gamma = 0$); red dotted lines: infinite switching costs ($\gamma = +\infty$). The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for banks' bankruptcy ratios. The units on the vertical axes are percent deviations from the steady state levels for other variables.

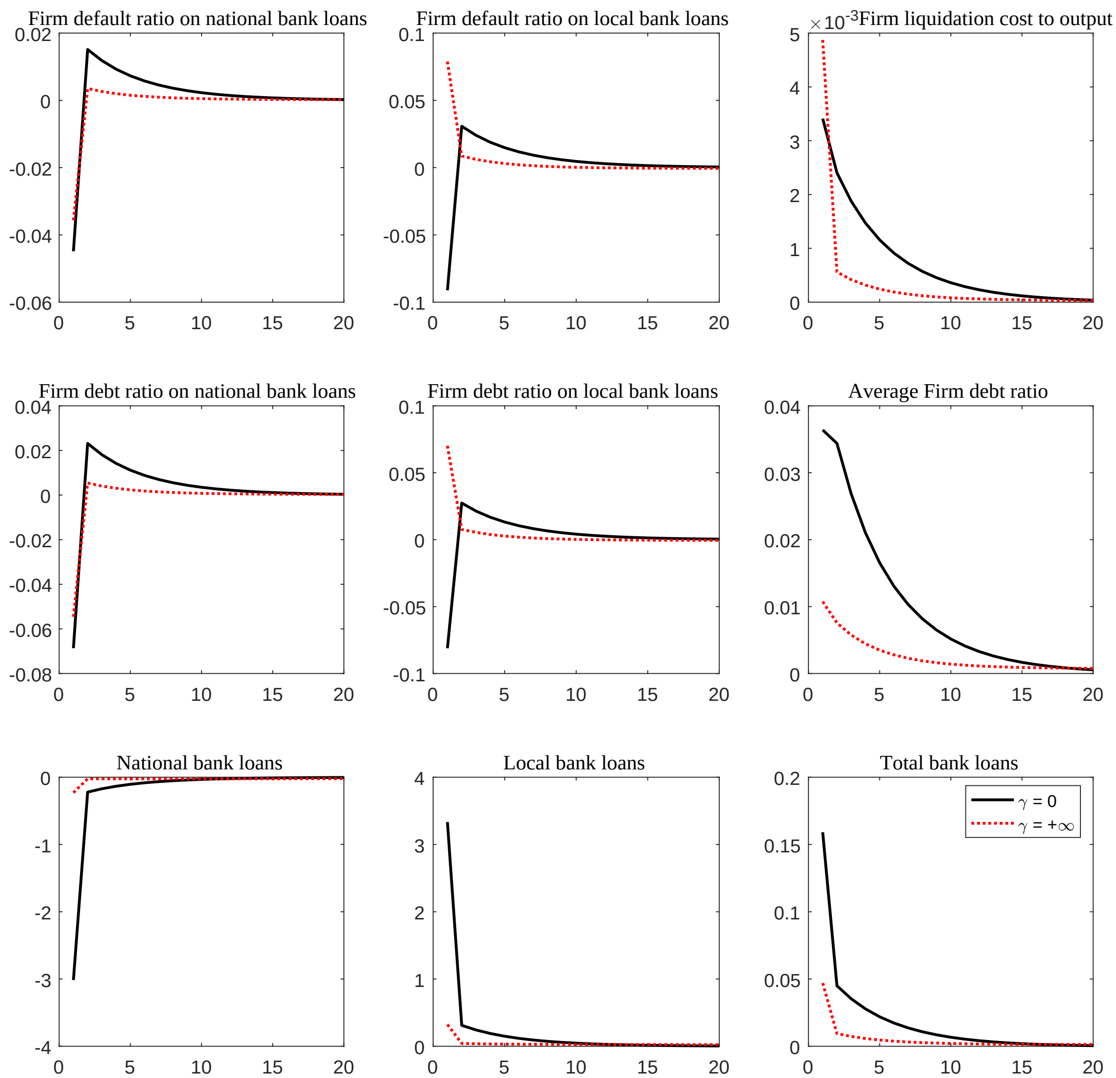

FIGURE B2. Impulse responses of a 1% negative RR shock on local banks ($\epsilon^l_{\tau,t} = -0.01$) for financial variables. Black solid lines: no switching costs ($\gamma = 0$); red dotted lines: infinite switching costs ($\gamma = +\infty$). The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for firms' default ratios, firms' debt ratios and firm liquidation cost to output ratio. The units on the vertical axes are percent deviations from the steady state levels for other variables.

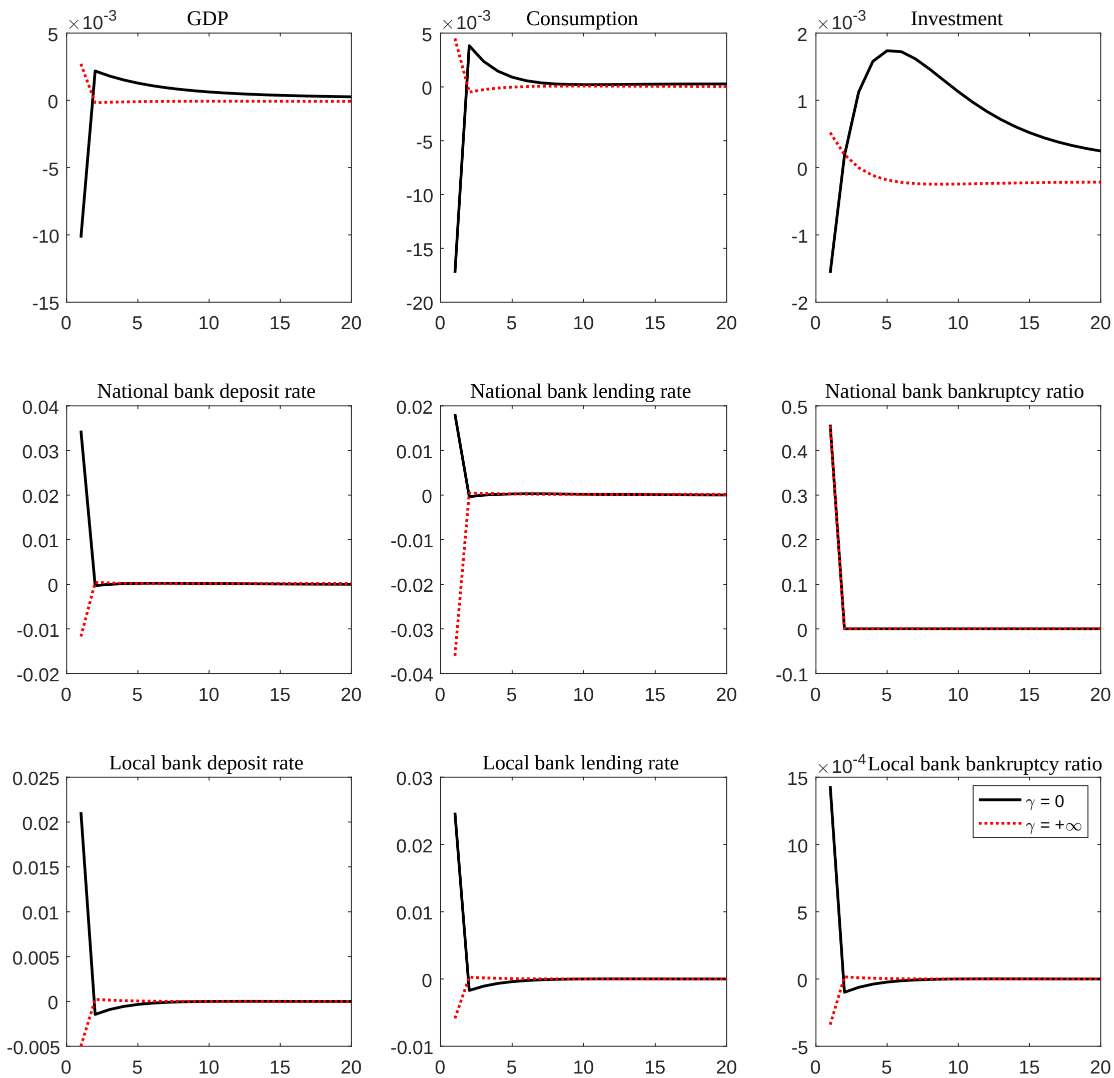

FIGURE B3. Impulse responses of a 1% negative RR shock on national banks ($\epsilon^{n}_{\tau,t} = -0.01$) for macroeconomic variables. Black solid lines: no switching costs ($\gamma = 0$); red dotted lines: infinite switching costs ($\gamma = +\infty$). The horizontal axes show the quarters after the impact period of the shock. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for banks' bankruptcy ratios. The units on the vertical axes are percent deviations from the steady state levels for other variables.

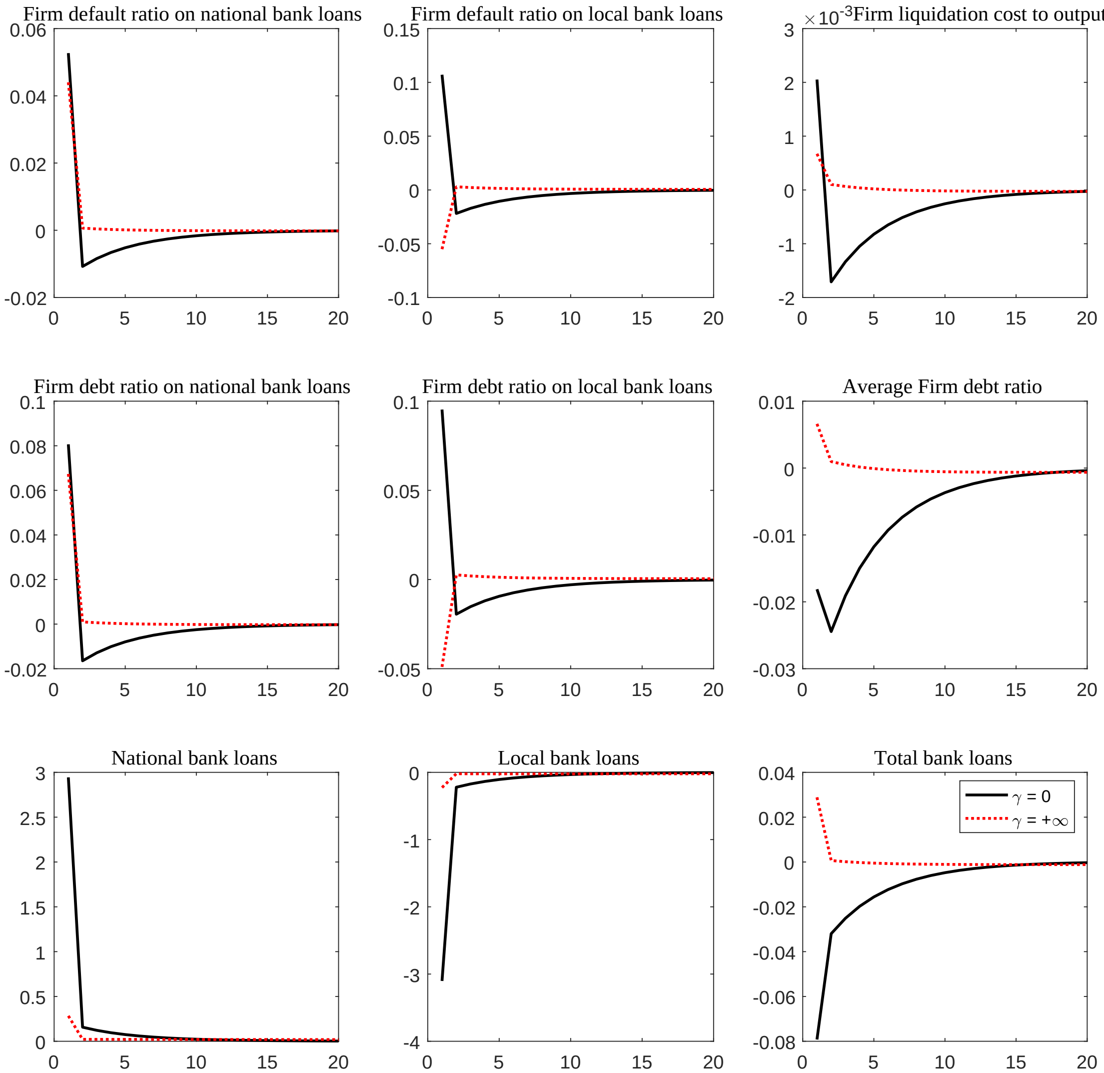

FIGURE B4. Impulse responses of a 1% negative RR shock on national banks ($\epsilon^n_{\tau,t} = -0.01$) for financial variables. Black solid lines: no switching costs ($\gamma = 0$); red dotted lines: infinite switching costs ($\gamma = +\infty$). The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for firms' default ratios, firms' debt ratios and firm liquidation cost to output ratio. The units on the vertical axes are percent deviations from the steady state levels for other variables.

Appendix B. Additional Figures

We first consider a relatively small negative technology shock $\epsilon_{at} = -0.01$. Figure B5 and B6 display the impulse responses to that shock under the three policy rules.

Under the benchmark regime, a negative technology shock reduces firms' return to investment, imposing upward pressure on firm default possibilities and credit spreads at existing lending levels. In response to higher spreads and reduced profitability, firms respond by reducing their leverage ratio. This leads to reduced returns on equity.

Firms that borrow from local banks are more negatively affected than those that borrow from national banks. Local banks, due to their monitoring advantages, have higher steady state leverage and default probabilities. This leaves local bank terms more sensitive to adverse shocks than national banks. However, under the small technology shock the switching cost is too high, precluding firms borrowing from local banks from switching to national banks.

With no switching taking place, the decline in aggregate TFP leads to a fall in real GDP. In this case, the symmetric RR policy and the asymmetric RR policy are almost equally effective in stabilizing the output. In particular, the RR cut on both types of banks under the symmetric rule reduces the funding costs of both types of banks and mitigates the fall in real GDP by raising credit supply in both banking sectors. In contrast, the asymmetric cut that only reduces RR on local banks stimulates the credit supply by local banks more aggressively but raises bankruptcy probabilities in local banks.

Alternatively, consider a relatively large negative technology shock $\epsilon_{at} = -0.05$. Figure B7 and B8 displays the impulse responses to the shock in an economy.

Under the benchmark regime, the negative technology shock reduces all firms' return to equity, although more acutely for firms borrowing from local banks. In this case, the improvement in returns to equity from switching to national banks are large enough to cover the switching cost for some local bank borrowers. As a result, while total lending falls, national bank lending rises. The shift to national banks also lowers the average leverage ratio, further reducing total output.

Given the large shock, the RR cut on both types of banks helps to reduce all banks' funding costs and mitigates the fall in the real GDP. However, the asymmetric cut stabilizes the real GDP better than cutting RRs symmetrically across bank types. This is because the asymmetric RR cut lowers the local bank lending rate relative to that of national banks, preventing switching to national banks. By comparison, while the symmetric cut stimulates both types of bank lending, it does not raise the total credit as much because firms switch to national banks.

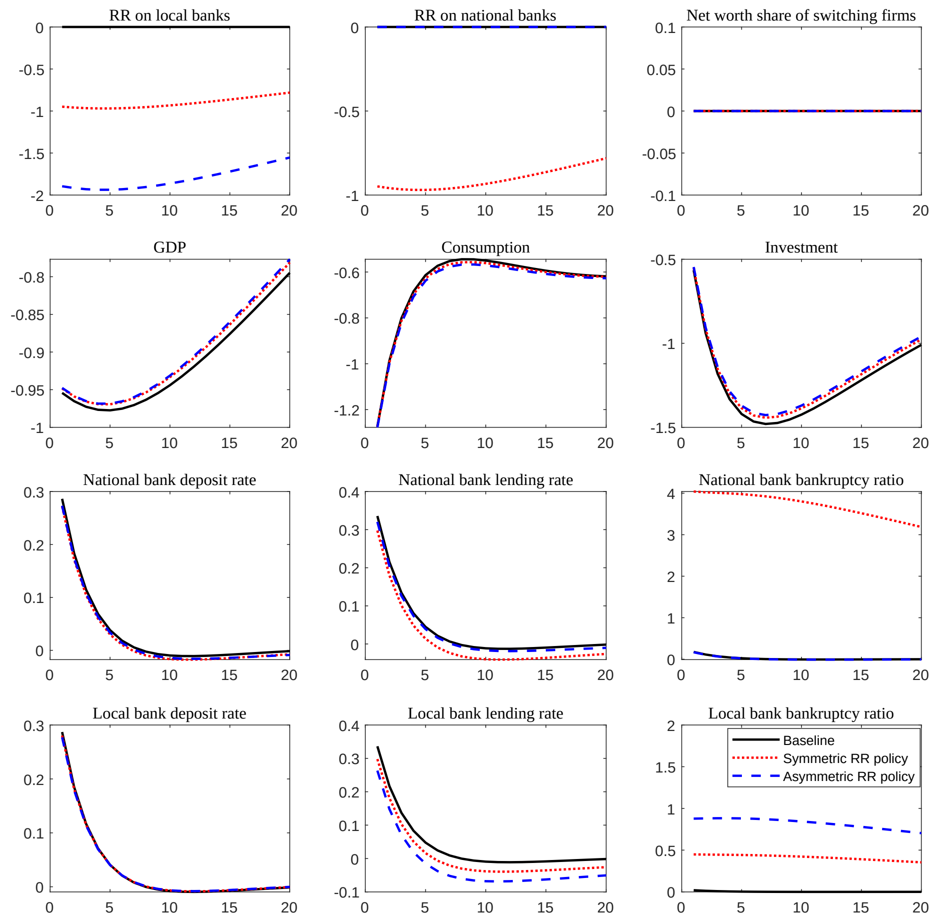

FIGURE B5. Impulse responses of aggregate variables to a small negative technology ($\epsilon_{at} = -0.01$) under alternative policy rules. Benchmark rule: black solid lines; symmetric RR rule: blue dashed lines; assymmetric rule: red dashed lines. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for RRs, net worth share of switching firms and banks' bankruptcy ratios. The units on the vertical axes are percent deviations from the steady state levels for other variables. The variable "Net worth share of switching firms" refers to the ratio of the net worth of firms that switch from local banks to national banks to the net worth of all firms.

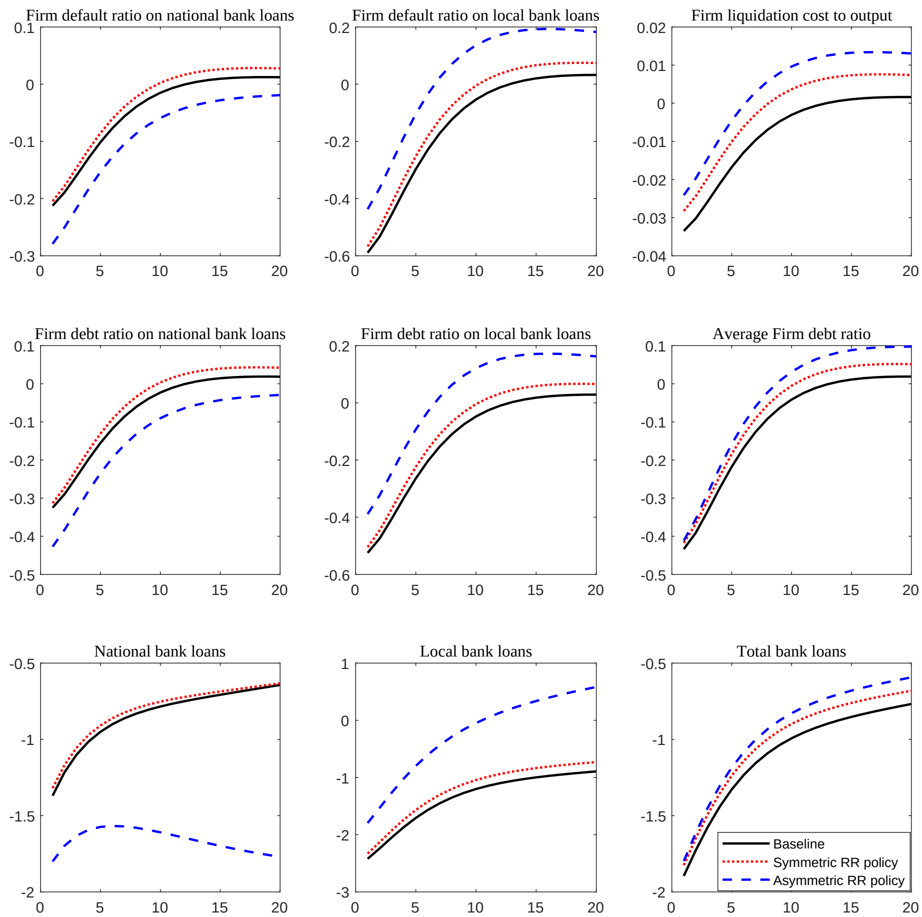

FIGURE B6. Impulse responses of financial variables to a small negative technology ($\epsilon_{at} = -0.01$) under alternative policy rules. Benchmark rule: black solid lines; symmetric RR rule: blue dashed lines; assymmetric rule: red dashed lines. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for firm default ratios, firm debt ratios and firm liquidation cost to output ratio. The units on the vertical axes are percent deviations from the steady state levels for other variables.

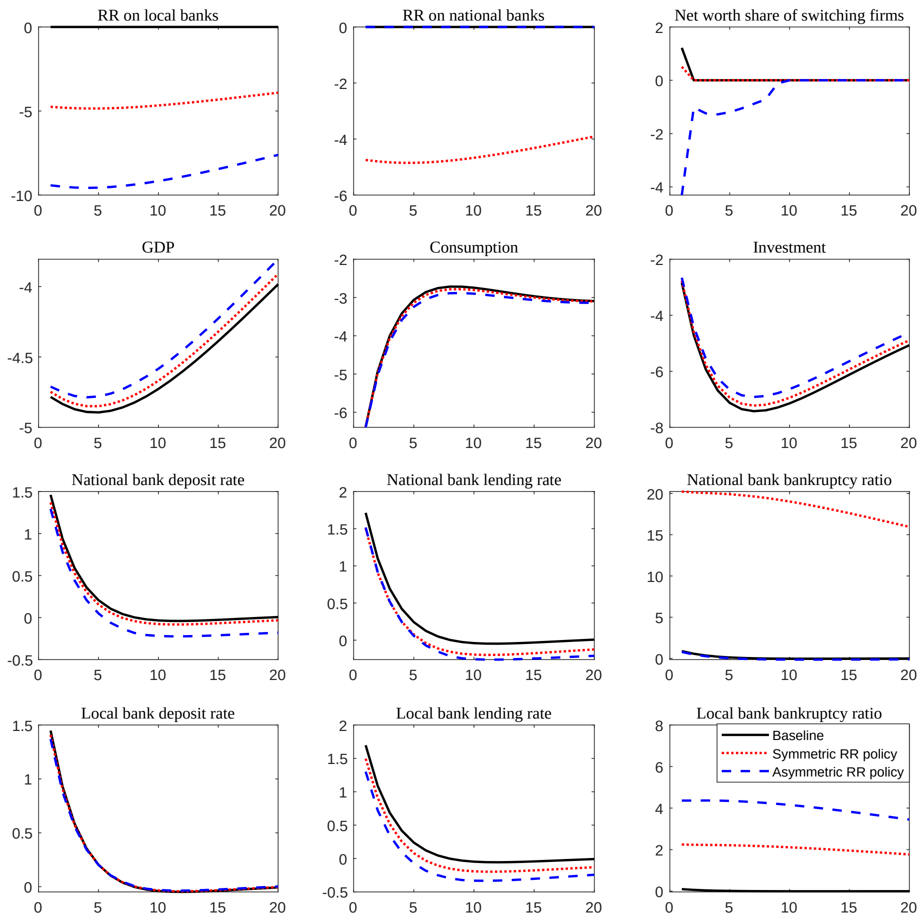

FIGURE B7. Impulse responses of aggregate variables to a large negative technology ($\epsilon_{at} = -0.05$) under alternative policy rules. Benchmark rule: black solid lines; symmetric RR rule: blue dashed lines; assymmetric rule: red dashed lines. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for RRs, net worth share of switching firms and banks' bankruptcy ratios. The units on the vertical axes are percent deviations from the steady state levels for other variables. The variable "Net worth share of switching firms" refers to the ratio of the net worth of firms that switch from local banks to national banks to the net worth of all firms.

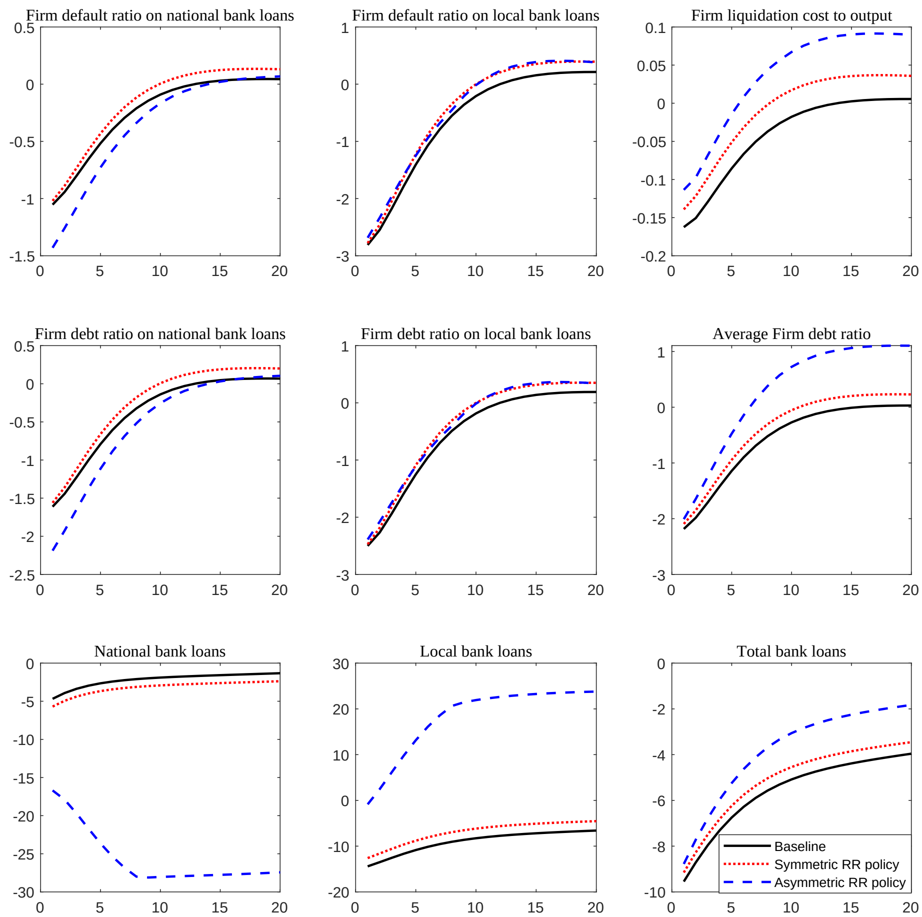

FIGURE B8. Impulse responses of financial variables to a small negative technology ($\epsilon_{at} = -0.01$) under alternative policy rules. Benchmark rule: black solid lines; symmetric RR rule: blue dashed lines; assymmetric rule: red dashed lines. The horizontal axes show the quarters after the impact period of the shock. The units on the vertical axes are percentage-point deviations from the steady state levels for firm default ratios, firm debt ratios and firm liquidation cost to output ratio. The units on the vertical axes are percent deviations from the steady state levels for other variables.

Appendix C. Threshold level to identify large shocks (D)

We set the threshold level D to minimize the out-of-sample mean squared error based on the subsample estimates. We use the following procedure to calculate the out-of-sample mean squared error for a given threshold level D.

(a) We begin by randomly taking out 10% of our full-sample data as "out-of-sample" data and use the rest 90% of the data as "in-sample" data.

(b) We split the "in-sample" data into a "small-shock" subsample and a "large-shock" subsample using the threshold level D. Each subsample is then estimated with the baseline specification (49).

(c) We split the "out-of-sample" data into a "small-shock" subsample and a "large-shock" subsample using the threshold level D. For each subsample, we calculate the forecast error as the difference between the observed and the predicted value of the bank loan growth $\Delta L_{i,t}$ using the estimated coefficients in (b) for its counterpart subsample in the "in-sample" data.

(d) We calculate the out-of-sample mean squared error as the average of the sum of square of all the forecast errors from (c).

We repeat the above procedure for 100 times and average out the out-of-sample mean squared error of each time as the final estimate of the out-of-sample mean squared error for a given threshold level D. Table C1 reports our estimates of out-of-sample mean squared error under various threshold levels of large shocks (D). We can see that, the out-of-sample mean squared error reaches a local minimum of 0.026 at $D = 0.04$. Notably, $D = 0.01$ achieves a similar level of forecating accuracy as does $D = 0.04$. However, $D = 0.01$ implies that over 70% of the bank-year observations in our sample would be classified as in the "large shock" subsample, which is inconsistent with the concept of "large shock" in our paper.

Table C1. Out-of-sample mean squared error under various threshold levels of large shocks.

Threshold level of large shocks (D)	Out-of-sample mean squared error
0.01	0.026
0.02	0.037
0.03	0.028
0.04	0.026
0.05	0.033
0.06	0.084

Appendix D. Robustness checks for empirical results

Our baseline results are robust to unwinsorized data and alternative standard error. Specifically, Table D1 reports the estimated coefficients using unwinsorized data. Table D2 reports the estimated coefficients under alternative method of standard error calculations.

Table D1. Regression results using unwinsorized data.

Sample	(1)	$D = 0.04$		$D = 0.03$		$D = 0.05$	
		(2) Small shock	(3) Large shock	(4) Small shock	(5) Large shock	(6) Small shock	(7) Large shock
$\Delta Y_{j(i),t} \times SM_i$	1.571*	2.187*	6.046*	2.445	4.427**	2.072*	104.615***
	(0.821)	(1.229)	(3.151)	(1.587)	(1.862)	(1.178)	(14.651)
$D/A_{i,t-1}$	0.488***	0.492***	−0.495	0.506***	−0.272	0.502***	0.384**
	(0.070)	(0.086)	(0.512)	(0.094)	(0.460)	(0.083)	(0.151)
$E/A_{i,t-1}$	1.294***	1.356***	1.853**	1.392***	1.279*	1.331***	4.419***
	(0.446)	(0.492)	(0.778)	(0.528)	(0.762)	(0.478)	(0.869)
$NPL_{i,t-1}$	−0.007**	−0.005*	−0.092*	−0.006	−0.012	−0.005*	−0.038
	(0.003)	(0.003)	(0.053)	(0.004)	(0.011)	(0.003)	(0.037)
$INT/A_{i,t-1}$	−0.936**	−1.817	−0.642***	−2.210	−0.661***	−1.002**	11.740***
	(0.462)	(1.257)	(0.152)	(1.387)	(0.248)	(0.490)	(2.917)
$L/A_{i,t-1}$	−0.825***	−0.826***	−0.710***	−0.847***	−0.873***	−0.845***	−0.469*
	(0.123)	(0.147)	(0.228)	(0.161)	(0.188)	(0.143)	(0.242)
Constant	0.182***	0.188***	1.591**	0.191***	0.792*	0.163***	−2.063***
	(0.053)	(0.066)	(0.750)	(0.064)	(0.472)	(0.053)	(0.443)
Sample size	2706	2291	415	2103	603	2415	291
Adjusted R-square	0.35	0.31	0.69	0.29	0.57	0.32	0.88

Note: The dependent variable is $\Delta L_{i,t}$ in all specifications. Bank dummies Z_i, year dummies θ_t, province-year dummies $P_j \times \theta_t$, small-bank-year dummies $SM_i \times \theta_t$ are included in all specifications. A bank-year observation is classified in the large (small) shock subsample if the bank locates in the province whose real GDP growth in current year deviates from its historical average by more (less) than a threshold level D. Standard error clustered at the bank level are shown in parentheses. Statistical significance levels are indicated by the asterisks: $^{***}: p < 0.01$, $^{**}: p < 0.05$, and $^{*}: p < 0.10$.

Table D2. Regression results using alternative standard errors.

Sample	(1)	$D = 0.04$		$D = 0.03$		$D = 0.05$	
		(2) Small shock	(3) Large shock	(4) Small shock	(5) Large shock	(6) Small shock	(7) Large shock
$\Delta Y_{j(i),t} \times SM_i$	1.212	1.318	2.995**	1.196	3.404**	1.333	10.183***
	(0.784)	(1.059)	(1.172)	(1.300)	(1.503)	(1.024)	(2.485)
$D/A_{i,t-1}$	0.395***	0.398***	0.162	0.396***	0.173	0.396***	0.304***
	(0.054)	(0.067)	(0.144)	(0.070)	(0.134)	(0.064)	(0.090)
$E/A_{i,t-1}$	1.070***	1.104***	1.551**	1.092***	1.321**	1.087***	2.619***
	(0.229)	(0.254)	(0.718)	(0.249)	(0.510)	(0.242)	(0.398)
$NPL_{i,t-1}$	−0.007**	−0.007**	−0.022	−0.007*	−0.004	−0.007**	−0.016
	(0.003)	(0.003)	(0.031)	(0.004)	(0.007)	(0.003)	(0.032)
$INT/A_{i,t-1}$	−0.503**	−0.764	−0.668***	−1.011	−0.528**	−0.579***	8.865***
	(0.208)	(0.558)	(0.123)	(0.595)	(0.246)	(0.191)	(1.151)
$L/A_{i,t-1}$	−0.665***	−0.668***	−0.559***	−0.663***	−0.663***	−0.666***	−0.415**
	(0.094)	(0.115)	(0.147)	(0.119)	(0.121)	(0.109)	(0.178)
$Constant$	0.172***	0.171***	0.371*	0.186***	0.402**	0.261***	−0.457***
	(0.040)	(0.059)	(0.191)	(0.063)	(0.170)	(0.025)	(0.116)
Sample size	2706	2291	415	2103	603	2412	294
Adjusted R-square	0.37	0.36	0.72	0.33	0.58	0.37	0.78

Note: The dependent variable is $\Delta L_{i,t}$ in all specifications. Bank dummies Z_i, year dummies θ_t, province-year dummies $P_j \times \theta_t$, small-bank-year dummies $SM_i \times \theta_t$ are included in all specifications. A bank-year observation is classified in the large (small) shock subsample if the bank locates in the province whose real GDP growth in current year deviates from its historical average by more (less) than a threshold level D. Standard error clustered at the province level are shown in parentheses. Statistical significance levels are indicated by the asterisks: $^{***}: p < 0.01$, $^{**}: p < 0.05$, and $^{*}: p < 0.10$.