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Xiaoming Li
University of International Business and Economics, China

Zheng Liu
Federal Reserve Bank of San Francisco

Yuchao Peng
Central University of Finance and Economics, China

Zhiwei Xu
Fudan University, China

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BANK RISK-TAKING, CREDIT ALLOCATION, AND MONETARY POLICY TRANSMISSION: EVIDENCE FROM CHINA

XIAOMING LI, ZHENG LIU, YUCHAO PENG, AND ZHIWEI XU

Abstract. Using confidential loan-level data from a large Chinese bank, we examine how Basel III implementation influenced the responses of bank risk-taking to monetary policy shocks. We use a difference-in-differences (DID) approach, exploiting disparities in lending behavior between high- and low-risk bank branches before and after the new regulations. Our findings reveal a novel risk-weighting channel through which monetary policy easing significantly reduced bank risk-taking. However, this risk reduction was achieved by shifting lending towards ostensibly low-risk state-owned enterprises (SOEs) with government guarantees, despite their lower average productivity. Our findings suggest a tradeoff facing China's monetary policy between curbing bank risks and addressing credit misallocation.

I. Introduction

In response to the 2008-09 Global Financial Crisis and the recent COVID-19 pandemic, central banks aggressively eased monetary policy to mitigate recessions. Such policy interventions, however, raised concerns about financial stability. If the policy interest rate remains persistently low, it has the potential to fuel asset price booms, leading to excessive leverage and risk-taking by financial institutions (Stein, 2013; Bernanke, 2020).

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Li: University of International Business and Economics, China; Email: xmLI.15@saif.sjtu.edu.cn. Liu: Federal Reserve Bank of San Francisco; Email: Zheng.Liu@sf.frb.org. Peng: Central University of Finance and Economics, China; Email: yuchao.peng@cufe.edu.cn. Xu: Fudan University, China; Email: xuzhiwei09@gmail.com. For helpful comments, we thank the Co-Editor (Şebnem Kalemli-Özcan), three anonymous referees, Saki Bigio, Catherine Casanova, Kaiji Chen, Hanming Fang, John Fernald, Linda Goldberg, Yi Huang, Huiyu Li, Wei Li, Yan Liu, Robert Marquez, Frank Packer, Alessandro Rebucci, Ilhyock Shim, Michael Song, Mark Spiegel, Shang-Jin Wei, Tao Zha, and seminar participants at CKGSB, CUFE, DUFE, Fudan, PKU, SAIF at SJTU, SWUFE, the Cleveland Fed, the San Francisco Fed, the 2021 ABFER-CEBRA conference, the 2021 Asian Meeting of the Econometric Society, the 2021 China Meeting of the Econometric Society, the 2021 China International Conference on Macroeconomics (CICM), and the 2021 CEBRA conference. We are grateful to Anita Todd for editorial assistance. 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.

Monetary policy can influence financial conditions and ultimately real economic activity by changing the risk appetite of financial intermediaries. Borio and Zhu (2012) coined the term "risk-taking channel" of monetary policy to describe this transmission mechanism. In theory, the link between monetary policy and risk-taking can be ambiguous. For example, the standard portfolio choice models suggest that lowering the short-term real interest rate could induce banks to reduce holdings of safe securities and thus increase risk-taking. Lower interest rates can also expand banks' risk-taking capacity by boosting bank profitability and net worth (Adrian and Shin, 2010). Risk-shifting models, in contrast, predict the opposite. In those models, asymmetric information between banks and borrowers combined with banks' limited liability create an agency problem (Stiglitz and Weiss, 1981). A reduction in deposit interest rates following monetary policy easing can alleviate the agency problem. Banks respond to the decline in funding costs by raising the share of lending to safer borrowers. The effects of monetary policy on risk-taking may also depend on banks' capital structure and leverage (Dell'Ariccia et al., 2014). Furthermore, monetary policy can lead to risk-shifting across different financial intermediaries, resulting in non-linear effects on risk-taking depending on the prevailing level of the interest rate (Coimbra and Rey, 2023).

The theoretical ambiguity renders the link between monetary policy and bank risk-taking an empirical question. This paper makes two contributions that shed lights on this important empirical issue. First, we document loan-level evidence that, through a novel risk-weighting channel, monetary policy easing in China reduced bank risk-taking under the Basel III capital regulations implemented in 2013. Second, we present evidence that monetary policy easing led to credit misalloation, because banks reduce risk-taking by raising the share of lending to SOEs that receive high credit ratings under government guarantees, despite their lower average productivity than private firms.

In China, bank lending is the primary source of financing for firms. Thus, changes in banking regulations can have important implications for the transmission of monetary policy to the real economy. In January 2013, China implemented the Basel III capital regulations. The new regulation raised the minimum capital adequacy ratio (CAR) and more importantly, it introduced a new internal ratings-based approach (IRB) for six large banks that increased the sensitivity of risk-weighted assets to credit risks of bank loans.[1]

[1]The six banks that implemented the IRB approach include the "Big Five" banks plus China Merchants Bank. The Big Five banks include the Industrial and Commercial Bank of China (ICBC), the Bank of China (BOC), the Construction Bank of China (CBC), the Agricultural Bank of China (ABC), and the Bank of Communications (BCM). According to the China Banking Regulatory Commission, the Big Five banks accounted for approximately half of the total loans in the banking sector.

We examine how the Basel III capital regulations could affect the link between bank risk-taking and monetary policy, both theoretically and empirically. We first present a simple theoretical model to highlight a risk-weighting mechanism. In the model, banks optimize loan portfolios subject to reserve requirements (RR) and a CAR constraint. In line with the Basel III regulations, the bank's risk-weighted assets are sensitive to loan risks. We obtain several important analytical results from the model. First, a binding CAR constraint leads to a negative relation between bank leverage and loan risks. Second, following an expansionary monetary policy shock (e.g., a decline in RR), banks choose to increase leverage; to comply with the CAR requirements, they have to reduce portfolio risks. Third, raising the risk-weighting sensitivity amplifies the reduction in bank risk-taking in response to monetary policy easing. Fourth, banks facing higher idiosyncratic risks would reduce risk-taking more aggressively in response to monetary policy easing.

Guided by theory, we use a difference-in-differences (DID) identification approach for our empirical analysis. We use confidential loan-level data from one of the "Big Five" commercial banks in China. We obtained detailed information on each individual loan, including information on the quantity, the price, and the credit rating of each loan. To construct firm-level controls in our empirical specifications, we merge the loan-level data with the firm-level data from China's Annual Survey of Industrial Firms (ASIF) obtained from the National Bureau of Statistics (NBS) of China.[2] We merge the two data sources by matching firm names and obtain about 330,000 unique firm-loan pairs from 2008 to 2017. We use the merged data to estimate how the implementation of the Basel III regulations in 2013 affected the responses of bank risk-taking to monetary policy shocks (compared to the pre-2013 period).

A practical challenge for estimating the effects of monetary policy shocks on risk-taking using loan-level data from a single large bank is that bank branches do not have control over the value of bank capital (the numerator of the CAR). However, in our sample, branches do have some control over their own risk-weighted assets (the denominator of the CAR). The bank headquarters sets credit ratings of individual borrowers and issues guidelines (or targets) on risk-weighted assets for each branch. A branch can meet the target by adjusting the loan amount or the loan risk compositions based on the credit

[2]The ASIF contains information on all above-scale manufacturing firms in China, with a little under 4 million firm-year observations covering the period from 1998 to 2013. The ASIF provides detailed information about each individual firm, including the firm's ownership structure, employment, capital stocks, gross output, value-added, and some accounting information (balance sheets, profits, and cash flows).

ratings set by the headquarters.[3] Thus, our data still allows us to identify the effects of monetary policy shocks on risk-taking through the risk-weighting channel.

For empirical identification, we exploit changes in the cross-sectional variations in lending behaviors between high-risk and low-risk branches in response to a monetary policy shock after the implementation of the new regulations. We measure branch-specific risk history by the share of non-performing loans (NPL) before the Basel III regulations were put in place. We measure monetary policy shocks by the exogenous component of the M2 growth rate estimated from the regime-switching model of Chen et al. (2018). Following Dell'Ariccia et al. (2017), we measure risk-taking based on the credit ratings of loans, which reflect the bank's internal assessment of the ex ante credit risks for each borrower. Specifically, our measure of risk-taking, which is the dependent variable in our baseline specification, is a dummy indicator that equals one if the loan has high credit ratings (AA+ or AAA) and zero otherwise. The key independent variable is a triple interaction between a post-regulation dummy, our risk history indicator, and our measure of monetary policy shocks. We control for a set of various fixed effects.

Consistent with theory, we find that, after the Basel III regulations were implemented, an expansionary monetary policy shock reduces risk-taking for high-risk branches relative to low-risk branches. The estimated reductions in risk-taking are statistically significant and economically important. Our baseline estimation suggests that, under the new regulations, a one-standard-deviation positive shock to monetary policy raises the probability of lending to firms with high credit ratings by about 14% relative to the sample mean.

The main results are robust when we re-estimate the model using bank-level data, additional controls for loan demand conditions, a sub-sample that excludes SOEs, alternative measures of monetary policy shocks, alternative measures of branch risks, alternative sources of cross-sectional variations, or controls for other policy reforms such as interest-rate liberalization, deleveraging policy, and the anti-corruption campaign.

The risk-weighting mechanism at the micro level has important implications for monetary policy transmission at the macro level through a credit misallocation channel. Under prevailing policies in China, SOEs have easier access to bank credit than non-state firms (Song et al., 2011). With government guarantees (explicitly or implicitly), SOE loans are perceived as ex ante low-risk loans.[4] Thus, a bank can reduce risk-taking by increasing the share of SOE lending. However, SOEs have lower productivity on average than

[3] According to a confidential internal document, the guidelines from the bank headquarters on risk-weighted assets are issued to province-level branches, which are then trickled down to lower-level branches.

[4] Our evidence suggests that, on average, SOE loans receive higher credit ratings than non-SOE loans.

private firms (Hsieh and Klenow, 2009). Indeed, our evidence indicates that the *ex-post* performance of SOE loans—measured by the share of nonperforming or overdue loans—is significantly worse than the average after controlling for credit ratings. The SOEs' preferential credit access leads to over-investment by SOEs, reducing the marginal product of capital of SOEs relative to non-SOE firms (Song et al., 2011; Chang et al., 2016). An increase in the share of SOE lending would thus exacerbate SOE over-investment, reducing aggregate productivity (Liu et al., 2021b).

Our evidence suggests that the nexus between capital regulations, risk-taking, and credit misallocation is important for the transmission of monetary policy shocks in China. We find that, in the post-Basel III periods, monetary policy easing significantly raised the share of SOE lending. Furthermore, at the province level, monetary policy easing significantly reduced the growth rate of total factor productivity (TFP) under Basel III relative to the pre-2013 period, consistent with the misallocation effects of monetary policy.

Our work adds to the empirical literature that highlights the importance of bank capital regulations for the risk-taking channel of monetary policy. For example, Jiménez et al. (2014) use Spanish loan-level data to show that, following a decline in short-term interest rates, less capitalized banks are more likely to increase lending to ex-ante risky borrowers, reflecting a search-for-yield effect. Dell'Ariccia et al. (2017) use U.S. loan-level data and document evidence that lower short-term interest rates are associated with more risk-taking, and this negative relation is stronger for better capitalized banks, reflecting the risk-shifting effect. Caglio et al. (2021) use firm-bank matched administrative data for the U.S. and show that monetary policy expansions lower the marginal cost of funds for small and risky firms and expand their borrowing capacity because those firms rely on procyclical earnings as collateral. Their study highlights a credit-demand channel of monetary policy. We contribute to this empirical literature by highlighting a new channel—a risk-weighting channel—through which monetary policy shocks can influence bank risk-taking. Our baseline estimation suggests that, after the implementation of Basel III regulations in China, bank risk-taking declined in response to an expansionary monetary policy shock. Complementary to the study of Caglio et al. (2021), we further show that the responses of risk-taking to monetary policy shocks in our sample reflect a credit-supply effect.[5]

[5]Other studies that document evidence on the risk-taking effects of monetary policy include, for example, Maddaloni and Peydró (2011), Bruno and Shin (2015), Delis et al. (2017), Bonfim and Soares (2018), and Kalemli-Özcan (2019).

Our finding of the misallocation effects of monetary policy using Chinese data echoes those of Gopinath et al. (2017), who document evidence of significant productivity losses in Spanish firms associated with the euro convergence process between 1999 and 2012. They show that, as the real interest rate in the euro area declined, capital inflows are misallocated toward Spanish firms with higher net worth but not necessarily higher productivity. Complementary to their study, we show that monetary policy easing can lead to credit misallocation through a novel risk-weighting channel. Following an expansionary monetary policy shock, banks reduce risk-taking by increasing the share of lending to SOEs. Such changes in lending behaviors exacerbate credit misallocation because SOEs have higher credit ratings but not necessarily higher productivity.[6]

Our work is also closely related to Chen et al. (2018), who emphasize a regulatory arbitrage channel through which China's monetary policy can affect banking risks. They show that, following a contractionary monetary policy shock, non-state banks shift lending from regulated on-balance-sheet loans toward unregulated shadow banking activities, raising risks for the banking system. Our evidence also suggests that a contractionary monetary policy shock raises bank risk-taking, but through the risk-weighting channel, which operates through shifting lending between low-risk loans and high-risk loans, both types are on the bank balance sheets.

To our knowledge, the risk-weighting channel for monetary policy transmission under capital regulations and the consequent misallocation effects are new to the literature.

II. A simple theoretical model of bank risk-taking

This section presents a simple partial equilibrium model to illustrate how bank capital regulations affect the responses of bank risk-taking to monetary policy shocks.

II.1. **The baseline model.**

The economy has a competitive banking sector, with a continuum of risk-neutral banks. Each bank has an endowment of net worth $e > 0$ units of goods. A bank takes deposits d from households at the risk-free deposit rate r_d. Under reserve requirements (RR), the bank can invest up to k units of assets (i.e., loans) in a risky project, subject to the flow-of-funds constraint

$$k + m = e + d, \tag{1}$$

[6]A partial list of recent studies that highlight the misallocation effects of macroeconomic policies includes Song et al. (2011), Reis (2013), Hsieh and Song (2015), Chang et al. (2016), Bleck and Liu (2018), Chang et al. (2019), Cong et al. (2019), Gao et al. (2019), Liu et al. (2021a), Chen et al. (2020), Huang et al. (2020), and Liu et al. (2021b).

where m denotes the amount of reserves, satisfying the RR constraint

$$m \geq \theta d, \tag{2}$$

where $\theta \in (0,1)$ is the reserve requirement ratio. For simplicity, we interpret exogenous variations in the RR ratio θ as a monetary policy shock, consistent with the quantity-based monetary policy practice in China (Chen et al., 2018). A decline in θ indicates a monetary easing.[7]

The risky project returns R units of goods for each unit of loans, where R is a random variable drawn from a uniform distribution with the cumulative density function $\mathbf{F}(R)$. We parameterize the distribution of R such that the mean and the variance are respectively given by

$$\mathbf{E}[R] = (\phi_1 - \phi_2\sigma)\,\sigma, \quad \mathbf{Var}[R] = \frac{1}{12}\sigma^2, \tag{3}$$

where $\phi_1, \phi_2 > 0$ are parameters. Each individual bank can choose a specific project indexed by $\sigma > 1$ from a set of feasible projects.

Our parameterization implies that the lower bound $\underline{R}(\sigma)$ and the upper bound $\bar{R}(\sigma)$ of the distribution $\mathbf{F}(R)$ are respectively given by

$$\underline{R}(\sigma) = \left(\phi_1 - \phi_2\sigma - \frac{1}{2}\right)\sigma, \quad \bar{R}(\sigma) = \left(\phi_1 - \phi_2\sigma + \frac{1}{2}\right)\sigma. \tag{4}$$

The cumulative density function is then a function of project risk σ and is given by

$$\mathbf{F}(R) = \frac{R - \underline{R}(\sigma)}{\bar{R}(\sigma) - \underline{R}(\sigma)} = \frac{R - \underline{R}(\sigma)}{\sigma}. \tag{5}$$

The distribution function implies the existence of an interior level of project risk, denoted by $\sigma^* = \frac{\phi_1}{2\phi_2}$, that maximizes the expected return. If $\sigma < \sigma^*$, the expected return $\mathbf{E}[R]$ monotonically increases with the risk parameter σ, implying a risk-return tradeoff, i.e., a higher risk is associated with a higher return. If $\sigma > \sigma^*$, a higher risk is associated with a lower return. In this case, the project is inefficient. We focus on an equilibrium with the risk-return tradeoff.

Each bank has limited liability, so it would exit the market if the realized profit falls below zero. Under deposit insurance, households receive risk-free returns on their deposits at the deposit rate r_d. The bank takes as given the deposit rate r_d, the RR ratio θ, and the stochastic project return R, and chooses σ, d, and m to solve the profit-maximizing problem

$$\max_{\{\sigma,d,m\}} V \equiv \int_{\underline{R}(\sigma)}^{\bar{R}(\sigma)} \max\{Rk + m - r_d d, 0\}\,\mathrm{d}\mathbf{F}(R), \tag{6}$$

[7]The qualitative results are the same if we consider the interest rate as the policy instrument.

subject to the flow-of-funds constraint (1), the RR constraint (2), and the CAR constraint

$$\frac{e}{\xi(\sigma)k + \xi_m m} \geq \tilde{\psi}. \tag{7}$$

Consistent with the Basel III regulations, the bank's CAR is measured by the ratio of bank capital e to the risk-weighted assets $\xi(\sigma)k + \xi_m m$, where $\xi(\sigma)$ denotes the risk-weighting function and ξ_m denotes the risk weight on the reserves. Since reserves held at the central bank are risk-free assets, we set $\xi_m = 0$, consistent with the CAR regulations under Basel III.[8] Under the CAR constraint (7), the bank is required to maintain a CAR above the minimum level of $\tilde{\psi}$.

The central bank pays zero interest on reserves, implying that the reserve requirements are binding, i.e., $m = \theta d$. Denote by $\lambda = \frac{k}{e}$ the risky leverage ratio, which is the ratio of risky assets k to the bank's net worth e. Without loss of generality, we refer to λ as the bank leverage.[9] The flow-of-funds constraint (1) implies that the bank's deposit satisfies $d = \frac{\lambda-1}{1-\theta}e$. The CAR constraint (7) is equivalent to a leverage constraint, satisfying

$$\lambda \leq \frac{1}{\tilde{\psi}\xi(\sigma)}. \tag{8}$$

We parameterize the risk-weighting function such that $\xi(\sigma) = \mu\sigma^{\rho}$, where $\mu > 0$ and $\rho \in (0, 1)$.

The effects of the CAR regulations on bank lending are characterized by the two parameters $\tilde{\psi}$ and ρ, with $\tilde{\psi}$ capturing the regulations on the level of capitalization and ρ measuring the sensitivity of bank assets to loan risks. Our parameterization of the risk-weighting function $\xi(\sigma) = \mu\sigma^{\rho}$ implies a greater penalty to riskier loans in the bank's portfolio, such that each asset is assigned a unique risk weight, reflecting in a reduced form the essence of the IRB approach under Basel III.

To characterize the bank's portfolio decisions, we rewrite the bank's objective function as

$$\max_{\{\sigma,\lambda\}} V \equiv e \int_{\underline{R}(\sigma)}^{\bar{R}(\sigma)} \max\{R\lambda - (\lambda - 1)r, 0\} \,\mathrm{d}\mathbf{F}(R), \tag{9}$$

where $r \equiv \frac{r_d-\theta}{1-\theta} > r_d$ is the bank's effective funding cost under RR. With limited liability and assuming a binding CAR constraint, there exists a break-even level of project return $R^*(\lambda(\sigma))$ such that the bank remains solvent if and only if the realized return $R \geq$

[8] The risk weight $\xi(\sigma)$ is a function of the project risk σ. To the extent that loan default risks and the potential default costs increase with the effective project risk, our assumption on the risk-weighting function is consistent with the IRB approach under Basel III.

[9] The total leverage ratio for a bank is given by $\frac{k+m}{e}$. Under a binding RR constraint, the risky leverage ratio λ is isomorphic to the total leverage ratio since $\frac{k}{e} = (\frac{k+m}{e} - 1)(1 - \theta) + 1$.

$R^*(\lambda(\sigma))$. The break-even project return is given by

$$R^*(\lambda(\sigma)) = r\left[1 - \frac{1}{\lambda(\sigma)}\right], \tag{10}$$

where $\lambda(\sigma) = \frac{1}{\psi\sigma^\rho}$ and $\psi \equiv \tilde{\psi}\mu$. Since the leverage λ strictly decreases with the risk σ, the cutoff of insolvency R^* strictly decreases with σ. A sufficient condition to ensure $R^*(\lambda) > \underline{R}(\sigma)$ is given by

$$\psi\bar{\sigma}^\rho < 1 - \frac{\left(\phi_1 - \frac{1}{2}\right)^2}{4\phi_2 r}, \tag{11}$$

where $\bar{\sigma} \equiv \arg\max_\sigma \underline{R}(\sigma) = \frac{\phi_1 - \frac{1}{2}}{2\phi_2} < \sigma^*$.

The bank's objective function can be equivalently written as

$$\begin{aligned}\max_{\{\sigma\}} V &\equiv e\lambda(\sigma)\int_{R^*(\lambda(\sigma))}^{\bar{R}(\sigma)} \left[R - R^*(\lambda(\sigma))\right] \mathrm{d}\mathbf{F}(R), \\ &= \max_{\{\sigma\}} e\lambda(\sigma)\left[\underbrace{\mathbf{E}(R) - R^*(\lambda(\sigma))}_{\text{asset-return benefit}} + \underbrace{\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))} \left(R^*(\lambda(\sigma)) - R\right) \mathrm{d}\mathbf{F}(R)}_{\text{risk-shifting benefit}}\right]\end{aligned} \tag{12}$$

where the unconditional expected return $\mathbf{E}(R)$ strictly increases with σ under our parameterization (with $\sigma < \sigma^*$). The term $e\lambda(\sigma)$ is the amount of total risky loans (k). The terms in the square brackets capture the profits produced by a marginal unit of risky loan, with two components. The first component $\mathbf{E}(R) - R^*(\lambda(\sigma))$ measures the expected interest income, that is, the expected project return net of the break-even return. The second component $\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))} (R^*(\lambda(\sigma)) - R)\, \mathrm{d}\mathbf{F}(R)$ reflects the benefits from risk-shifting under limited liability: if the realized project return falls below the break-even return, the bank can default on its liabilities.

We focus on an interior solution to the bank portfolio choice problem and project risk parameter such that $\sigma \in (0, \sigma^*)$. The first-order condition for the optimizing choice of σ is given by

$$\frac{\partial V}{\partial \sigma} + \frac{\partial V}{\partial \lambda}\frac{\partial \lambda}{\partial \sigma} = 0. \tag{13}$$

The first term in the above optimal condition, $\frac{\partial V}{\partial \sigma}$, indicates the direct marginal effect of the project risk on the bank's expected profit, holding the leverage λ constant. From the bank's objective function (12), this direct marginal effect is given by

$$\frac{\partial V}{\partial \sigma} = e\lambda(\sigma)\left\{\underbrace{\frac{\partial\left[\mathbf{E}(R)\right]}{\partial \sigma}}_{\text{asset-return margin}} + \underbrace{\frac{\partial}{\partial \sigma}\left[\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))} \left(R^*(\lambda(\sigma)) - R\right) \mathrm{d}\mathbf{F}(R)\right]}_{\text{risk-shifting margin}}\right\}. \tag{14}$$

Thus, holding the leverage constant, changes in the project risk (σ) can affect the bank's profit through two channels, one through the expected project return and the other through the risk-shifting benefit under limited liability. In the Online Appendix S.1.2, we show that the sum of the two effects is positive for any $\sigma \in (0, \sigma^*)$. That is, an increase in the loan risk raises the sum of the expected investment return and the benefit of risk-shifting. Then, we have $\frac{\partial V}{\partial \sigma} > 0$.

The second term in the optimal condition (13), $\frac{\partial V}{\partial \lambda}\frac{\partial \lambda}{\partial \sigma}$, captures the indirect effects of changes in the project risk on bank profit through responses of the leverage λ under the CAR constraint. The marginal effect of leverage on bank profit is given by

$$\frac{\partial V}{\partial \lambda} = \underbrace{e\left[\mathbf{E}(R) - r + \int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))} \left(R^*(\lambda(\sigma)) - R\right) \mathrm{d}\mathbf{F}(R)\right]}_{\text{asset-return margin}} + \underbrace{e\lambda \frac{\partial}{\partial \lambda}\left[\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))} \left(R^*(\lambda(\sigma)) - R\right) \mathrm{d}\mathbf{F}(R)\right]}_{\text{risk-shifting margin}}. \tag{15}$$

A rise in leverage can increase the expected profit by raising the interest income (the first term) or raising the risk-shifting benefit because of a higher insolvency probability (the second term).

Under the risk-sensitive CAR constraints, an increase in the portfolio risk σ depresses leverage, i.e., $\frac{\partial \lambda}{\partial \sigma} = -\frac{\rho}{\psi \sigma^{\rho+1}} < 0$. A lower leverage, in turn, reduces the bank's profit, as indicated by Eq. (15). The overall effects of project risk on the bank profit through the leverage channel is given by $\frac{\partial V}{\partial \lambda}\frac{\partial \lambda}{\partial \sigma}$.

In our model, bank leverage and portfolio risks are both endogenous and negatively correlated under CAR constraints. This makes our model different from the standard models with leverage constraints, such as that studied by Dell'Ariccia et al. (2014). In our model, if leverage is fixed and thus independent of portfolio risks, then risk-taking (σ) would increase with the interest rate due to risk-shifting. This outcome is the same as the fixed leverage scenario for a highly leveraged bank in Dell'Ariccia et al. (2014), where leverage is invariant to project risk (i.e., $\frac{\partial \lambda}{\partial \sigma} = 0$). In this case, the indirect effect of project risk on bank profit through its effects on leverage would be muted, i.e., the second term in Eq. (13) is zero. Thus, the CAR constraint with risk-weighting in our model provides a new channel through which the bank's portfolio risks can endogenously affect its leverage.

With the uniform distribution of project returns, the first-order necessary conditions for the bank's portfolio-choice problem implies that the optimal level of project risk σ satisfies

$$\frac{1+\rho}{2\sigma}\left[\bar{R}(\sigma) - R^*(\lambda(\sigma))\right] = \frac{\partial\left[\bar{R}(\sigma) - R^*(\lambda(\sigma))\right]}{\partial \sigma}. \tag{16}$$

Increasing the project risk σ raises the interest income and thus raises the bank's profit. However, under the CAR constraint, increasing the project risk also reduces leverage and thus reduces profit. At the margin, the benefit from interest income equals the cost of reduced leverage, such that Eq. (16) holds.

The optimal choice of σ implies that tightening the CAR constraint by either raising the required level of capitalization (ψ) or increasing the risk sensitivity (ρ) would reduce risk-taking by the bank. This is because tightening the CAR constraint reduces the bank's leverage ratio, inhibiting its risk-taking ability. This result is formally stated in Lemma 1 of Appendix S.1.

Given the CAR constraint, an expansionary monetary policy (i.e., a decline in θ) boosts the incentive for the bank to increase leverage. Under a binding CAR constraint, a bank can increase leverage only if it reduces risk-taking. Furthermore, with a lower θ, the bank faces a lower funding cost and a lower break-even rate of return $R^*(\sigma) = r\,(1 - \psi\sigma^\rho)$. A lower R^* in turn implies a lower probability of insolvency, reducing the marginal benefit of risk-shifting (see Eq. (15)). Thus, the bank chooses to take less risk. These results are formally stated in Proposition 1.[10]

Proposition 1. In response to monetary policy easing (i.e., a decline in θ), the optimal leverage ratio $\lambda = \frac{k}{e}$ increases and the optimal level of risk σ decreases. That is,

$$\frac{\partial \lambda}{\partial \theta} < 0, \quad \frac{\partial \sigma}{\partial \theta} > 0. \tag{17}$$

Proof. See Appendix S.1. □

Changes in CAR regulations can affect how bank risk-taking responds to monetary policy shocks. In practice, China's implementation of Basel III beginning in 2013 introduced the IRB approach to calculating risk-weighted assets for assessing a bank's CAR, increasing the sensitivity of the CAR to credit risks. This aspect of the regulatory policy change corresponds to an increase in ρ in our model.[11]

[10] In our simple model here, bank decisions are static. In a more general environment with forward-looking banks, a bank would care about the value of future rents in its risk-taking decisions; that is, a charter value channel would be present (Keeley, 1990). When the effective funding cost falls such that interest income rises, a forward-looking bank would choose a safer portfolio to reduce the probability of project failures in future periods. In this sense, generalizing the model to incorporate the charter value channel would strengthen the relation between risk-taking and monetary policy that we establish in Proposition 1.

[11] The new regulations also raised the minimum bank capitalization level, corresponding to an increase in ψ in our model. In a regime with a higher ψ, a bank would have higher capitalization on average. Thus, monetary policy easing would still raise leverage and reduce risk-taking, but to a lesser extent. We formally prove this result in Lemma 2 of Appendix S.1.

In a regime with a higher ρ, the bank's leverage would become more sensitive to project risks. Thus, monetary policy easing would lead to a larger reduction in risk-taking. This implication depends crucially on the negative relationship between leverage and optimal project risk under a binding CAR constraint (i.e., $\frac{\partial \lambda}{\partial \sigma} = -\frac{\rho}{\psi \sigma^{\rho+1}} < 0$). The results is formally stated in Proposition 2.

Proposition 2. The risk-weighting sensitivity amplifies the responses of bank risk-taking to monetary policy (i.e., $\frac{\partial \sigma}{\partial \theta}$). Formally, we have

$$\frac{\partial^2 \sigma}{\partial \theta \partial \rho} > 0. \tag{18}$$

Proof. See Appendix S.1. □

In Figure S.1.1 of the Online Appendix, we provide a graphical illustration of how capital regulations under Basel III could affect bank risk-taking and its response to a monetary policy shock.

II.2. **Banks' idiosyncratic risks.** To enable empirical identification, cross-sectional heterogeneity is essential. We now extend our baseline theoretical model to incorporate such heterogeneity by introducing bank-specific idiosyncratic risks. As in the baseline model, an individual bank can choose a project indexed by its risk σ from a set of feasible projects. Each bank also faces an idiosyncratic risk denoted by Δ.[12]

Specifically, for a project with the risk σ selected by the bank with idiosyncratic risk Δ, the project return R is a random variable drawn from a uniform distribution with the cumulative density function $\mathbf{F}(R)$. The mean and the variance of R are respectively given by $\mathbf{E}[R] = (\phi_1 - \phi_2\sigma)\,\sigma$ and $\mathbf{Var}[R] = \frac{1}{12}(\sigma\Delta)^2$. The overall project risk consists of two components: an endogenous component σ that can be optimally chosen by the bank and an exogenous component $\Delta \geq 1$ that is bank specific and cannot be chosen. This parameterization implies that the lower bound $\underline{R}(\sigma, \Delta)$ and the upper bound $\bar{R}(\sigma, \Delta)$ of the uniform distribution $\mathbf{F}(R)$ are respectively given by $\underline{R}(\sigma, \Delta) = \left(\phi_1 - \phi_2\sigma - \frac{1}{2}\Delta\right)\sigma$ and $\bar{R}(\sigma, \Delta) = \left(\phi_1 - \phi_2\sigma + \frac{1}{2}\Delta\right)\sigma$. The implied cumulative density function is then given by $\mathbf{F}(R) = \frac{R - \underline{R}(\sigma,\Delta)}{\bar{R}(\sigma,\Delta) - \underline{R}(\sigma,\Delta)} = \frac{R - \underline{R}(\sigma,\Delta)}{\sigma\Delta}$. Under these assumptions of the distribution function, the idiosyncratic risk Δ affects the variance of the project returns, but not the mean. Thus, an increase in Δ represents a mean-preserving spread of the project returns.

[12]Our specification with banks' idiosyncratic risks is similar to the model of Gertler and Kiyotaki (2010), where a bank can make loans only to nonfinancial firms located on the same island, which is confronted with an island-specific idiosyncratic risk.

An individual bank with the idiosyncratic risk Δ takes as given the effective funding cost $r = \frac{r_d - \theta}{1-\theta}$ and the stochastic project return R, and chooses σ and λ to maximize profits subject to the CAR constraint

$$\frac{e}{\xi\left(\sigma\Delta\right)k} \geq \tilde{\psi}, \tag{19}$$

where $\xi\left(\sigma\Delta\right)$ denotes the risk-weighting function (after imposing a zero risk weight on reserves). We parameterize the risk-weighting function such that $\xi(\sigma\Delta) = \mu\left(\sigma\Delta\right)^{\rho}$, where $\mu > 0$ and $\rho \in (0,1)$. The rest of the model is identical to that in the baseline model.

The first-order condition for the bank's optimizing choice of σ implies that

$$\frac{1+\rho}{2\sigma}\left[\bar{R}\left(\sigma\right) - R^{*}\left(\sigma\right)\right] = \frac{\partial\left[\bar{R}\left(\sigma\right) - R^{*}\left(\sigma\right)\right]}{\partial\sigma} + \frac{1-\rho}{4}\left[\left(\Delta-1\right) - \frac{2}{\sigma}r\psi\sigma^{\rho}\left(\Delta^{\rho}-1\right)\right], \tag{20}$$

where $\bar{R}\left(\sigma\right)$ and $R^{*}\left(\sigma\right)$ are the upper bound of R and the threshold of insolvency when $\Delta = 1$. Eq. (20) shows that the model with bank-specific idiosyncratic risks nests the baseline model in the special case with $\Delta = 1$. The second term of the right-hand side of the equation captures the additional net benefit of risk-taking in the presence of idiosyncratic risks ($\Delta > 1$). An increase in Δ raises the marginal benefit of risk-taking by raising the interest income. However, an increase in Δ also tightens the CAR constraint, raising the marginal cost of risk-taking. In general, how idiosyncratic risks affect banks' risk-taking decisions can be ambiguous. Under some plausible parameter restrictions, in particular, with $\rho r\psi < \frac{1}{2}$, this additional term in Eq. (20) increases with Δ. In this case, bank-specific idiosyncratic risks encourage risk-taking, such that the optimal level of project risk σ increases with Δ. This result is formally stated in Proposition 3.

Proposition 3. Assume that $\rho r\psi < \frac{1}{2}$. The optimal project risk increases with bank-specific risks (Δ), that is

$$\frac{\partial\sigma}{\partial\Delta} > 0.$$

Proof. See Appendix S.1. □

As we have discussed in Proposition 2, in the baseline model with $\Delta = 1$, an increase in the risk-weighting sensitivity (ρ) reduces risk-taking conditional on monetary policy easing. In the more general case with $\Delta > 1$, an increase in ρ raises the sensitivity of bank leverage to both σ and Δ. Thus, the presence of idiosyncratic risks amplifies the sensitivity of risk-taking to changes in capital regulations (in particular, changes in ρ), both on average and conditional on monetary policy shocks. These results are formally stated in Proposition 4.

Proposition 4. A bank facing a greater level of idiosyncratic risks (Δ) reduces risk-taking (σ) more aggressively when regulations raise the risk-weighting sensitivity ρ. That is,

$$\frac{\partial^2 \sigma}{\partial \rho \partial \Delta} < 0. \tag{21}$$

Furthermore, under a higher level of risk-weighting sensitivity (e.g., when ρ increases from 0 to 1), a bank facing a higher idiosyncratic risk reduces risk-taking more aggressively following an expansionary monetary policy shock. In particular, we have

$$\frac{\partial}{\partial \Delta}\left[\frac{\partial \sigma}{\partial \theta}|_{\rho=1} - \frac{\partial \sigma}{\partial \theta}|_{\rho=0}\right] > 0. \tag{22}$$

Proof. See Appendix S.1. □

III. Empirical analysis

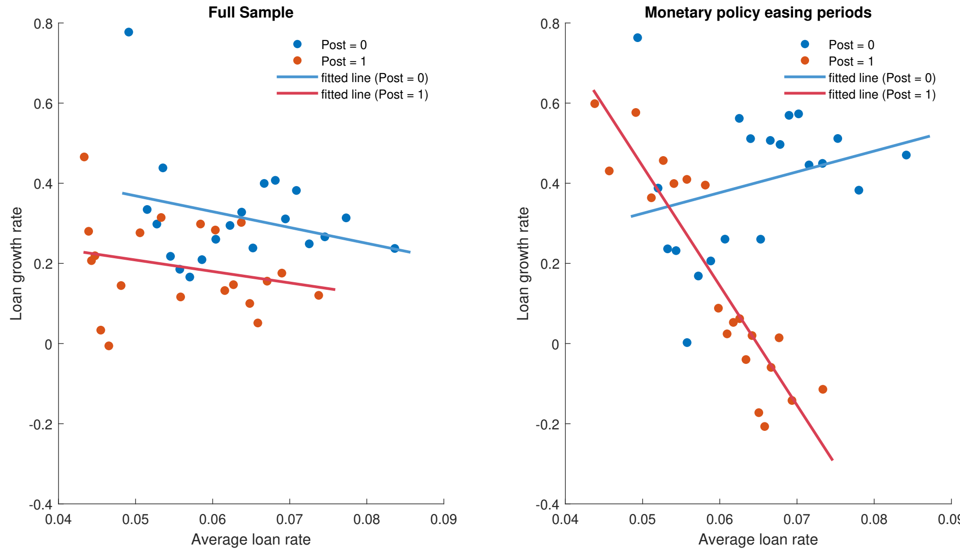
The theoretical model predicts that an expansionary monetary policy shock raises bank leverage; and to comply with the CAR constraints, banks need to reduce risk-taking in order to expand leverage. Increasing risk-weighting sensitivity amplifies the responses of risk-taking to monetary policy shocks, and the amplification effect is stronger for those banks facing higher idiosyncratic risks. We use these theoretical insights for our empirical identification. As we show below, the empirical evidence supports the model predictions.

III.1. **The data and some stylized facts.** We begin with descriptions of our micro-level data and some stylized facts in the data.

III.1.1. *The data.* We construct a unique micro data set using confidential loan-level data from one of China's Big Five commercial banks, merged with firm-level data in China's Annual Survey of Industrial Firms (ASIF). The loan-level data contain detailed information on each individual loan, including the quantity, the price, and the credit rating, among other indicators. To control for borrower characteristics in our empirical estimation, we merge the loan data with firm-level data taken from the ASIF, which covers all above-scale industrial firms from 1998 to 2013, with nearly 4 million firm-year observations.[13] The ASIF data contain detailed information on each individual firm, including the ownership structure, employment, capital stocks, gross output, value-added, firm identification (e.g., company ID), and complete information on the three major accounting statements (i.e., balance sheets, profit and loss accounts, and cash flow statements). In the absence of a consistent firm identification code, we merge the loan data

[13]From 1998 to 2007, the ASIF covered all SOEs regardless of their size and non-SOEs with annual sales above 5 million RMB. After 2007, the ASIF excluded small SOEs with annual sales below 5 million RMB. After 2011, the ASIF included only manufacturing firms with annual sales above 20 million RMB, regardless of their ownership status (SOE or non-SOE).

FIGURE 1. Relations between leverage and interest rates



Notes: The figure shows the bin-scatter plots of the relationship between branch-level leverage and loan interest rates before ($Post = 0$, blue dots) and after 2013 ($Post = 1$, red dots). The branch-level leverage is measured by the quarterly growth rate of the loan amount. The branch-level loan rate is measured by the average of individual loan rates weighted by the loan size. The observations are grouped by 20 bins of average loan interest rates. The left panel shows the full sample and the right panel shows the sub-sample with monetary policy easing. The blue and red lines are the linear fitted lines for the sub-sample periods before 2013 and those after, respectively.

with the firm data using firm names. The merged data set contains information on about 330,000 unique firm-loan pairs from 2008:Q1 to 2017:Q4, accounting for approximately half of the total amount of loans issued to manufacturing firms by the bank.

III.1.2. *The relations between leverage and interest rates.* The risk-taking channel in our theoretical model implies that, under the Basel III capital regulations, monetary policy easing would lead to an increase in bank leverage (see Proposition 1). If the increase in leverage reflects credit supply expansion, then we should also observe a decline in loan interest rates. This implication is consistent with our branch-level data, as shown in Figure 1.

The figure shows the correlations between branch-level leverage measured by loan growth (vertical axis) and the branch-level average interest rates (horizontal axis) for the full sample (left panel) and the sub-sample periods with monetary policy easing.[14]

[14] Since we do not have balance-sheet information at the branch level, we measure leverage by the quarterly growth rate of the loan amount. The branch-level interest rate is the average value of individual loan rates (weighted by the loan size) for each quarter.

In the full sample, there is a weak negative relation between leverage and interest rates, both before and after the implementation of Basel III in 2013. In the sub-sample with monetary policy easing, however, there was a steeper negative relation between leverage and interest rates after 2013, while the relation remained roughly flat (and slightly upward-sloping) before 2013. These observations suggest that, under the Basel III capital regulations, monetary policy boosts branch-level leverage through a credit supply channel, consistent with our theory.

III.1.3. *The relations between leverage and portfolio risks under Basel III.* Our theory implies a negative relation between bank leverage and portfolio risks under CAR constraints. This implication is also consistent with the data. Table 1 shows the regressions of branch-level portfolio risks on branch-level leverage for both the pre-2013 period (Column (1)) and the post-2013 period (Column (2)). Here, we measure portfolio risks by (the inverse of) the share of high-rating loans (i.e., those with ratings AA+ or AAA) in the total loan amount ($HighRShare_{j,t}$) and we measure leverage by loan growth. In the regressions, we control for the average loan size and the average loan interest rates (relative to the benchmark lending rates), as well as branch fixed effects and year-quarter fixed effects. The regressions suggest that there was no significant relations between portfolio risks and leverage before Basel III. However, under Basel III, branches with higher portfolio risks (i.e., those with lower shares of high-rating loans) had also lower leverage. This negative relation is consistent with the risk-weighting channel of our model.

III.2. **The empirical model and the estimation approach.** We now examine how changes in capital regulations affect the responses of bank risk-taking following a monetary policy shock. For this purpose, we estimate the empirical specification

$$\begin{aligned} HighR_{ijdpt} = {} & \alpha \times RiskH_j \times Post_y + \beta \times RiskH_j \times Post_y \times MP_t \\ & + \gamma \times RiskH_j \times MP_t + \theta \times X_i \times \mu_y + \eta_j + \mu_t + \zeta_d + \xi_p + \epsilon_{ijdpt}. \end{aligned} \tag{23}$$

In this specification, the dependent variable $HighR_{ijdpt}$ is a dummy variable indicating whether the loan has a high credit rating. Specifically, the dummy variable takes a value of one if loan i issued by city-level branch j to a firm in industry d, located in province p, and in quarter t is rated as AA+ or AAA, and zero otherwise. Hereafter, we refer to loans with high credit ratings (AA+ or AAA) as "high-rating loans."

We interpret the implementation of Basel III regulations, and in particular changes in the risk-weighting methods from the regulatory weighting (RW) approach to the IRB approach, as an exogenous event for bank branches. Basel III capital regulations apply

TABLE 1. Relations of portfolio risks with leverage

	(1) $HighRShare_{j,t}$ Before 2013	(2) $HighRShare_{j,t}$ After 2013
$LoanGrowth_{j,t}$	0.00743	0.00682**
	(0.00492)	(0.00276)
Controls	yes	yes
Branch FE	yes	yes
Year-quarter FE	yes	yes
Observations	3,064	3,306
R^2	0.588	0.564

Notes: This table reports the estimation results of the regression of the branch-level portfolio risks measured by (the inverse of) the share of high-rating loans ($HighRShare_{j,t}$) on branch-level leverage measured by loan growth ($LoanGrowth_{j,t}$), for the sub-sample before the implementation of Basel III in 2013 (Column (1)) and those after 2013 (Column (2)). $HighRShare_{j,t}$ is the share of high-rating loans (i.e., those rated AA+ or AAA) in the total amount of loans for branch j in period t. $LoanGrowth_{j,t}$ is the growth rate of the total loan amount for branch j in period t. The regressions control for the logarithm of the average loan size and the average loan interest rates (as percentage deviations from the benchmark lending rates), as well as the branch fixed effects and the year-quarter fixed effects. The numbers in the parentheses indicate robust standard errors double clustered at time and branch level. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

mainly at the bank group level. In practice, however, branches have discretion in managing risk-weighted assets to meet the target set by the bank headquarters. A branch can meet the target by adjusting the loan quantity or the loan risk-compositions based on the credit ratings set by the headquarters.[15] This empirical setup maps to our theoretical model, where the bank's net worth (e) is exogenous (corresponding to the capital at the bank group level, which is beyond the control of individual branches) and a branch

[15]According to an internal document issued in 2012 by the bank from which we obtained the loan-level data, bank branches "are responsible for implementing the annual risk-weighted asset control plan issued by the headquarters,... reporting the risk-weighted asset situation, cooperating with the construction of the risk-weighted asset measurement system, and organizing the implementation of risk-weighted asset management."

can choose the amount of loans (k) and the portfolio risks (σ) subject to the CAR constraint. We use the dummy variable $Post_y$ to indicate the post-2013 period under the new regulations: it equals one if the year is 2013 or later and zero otherwise.

Our theory predicts that, under given CAR regulations, monetary policy easing reduces bank risk-taking (Proposition 1); raising the sensitivity to risk-weighting amplifies the reduction in risk-taking following a monetary policy expansion (Proposition 2); and furthermore, the reductions in risk-taking following an expansionary monetary policy shock should be more pronounced for branches with higher idiosyncratic risks (Proposition 4).

Based on these theoretical implications, we implement a DID identification approach, exploiting the differential responses to regulatory changes between the high-risk and the low-risk branches to identify the impact of regulatory changes on risk-taking. We use the bank branches with a high average share of NPL prior to 2013 as the treatment group and the other branches as the control group. Specifically, we define the dummy variable $RiskH_j$, which equals one if branch j's average share of NPL in the period 2008-2012 is above the median, and zero otherwise. This classification of risk groups based on past NPL ratios is consistent with our theoretical model.

To ensure the validity of our identification approach, we conduct a mean test for the pre-2013 period to see whether the behavior of the treated group differed systematically from the control group before the new regulations were implemented. Table 2 compares several indicators of the lending behavior between the control group (i.e., the low-risk branches with NPL shares at or below the median) and the treatment group (i.e., the high-risk branches with NPL shares above the median). The table shows that the average differences in the behavior of these two groups prior to 2013 are small and statistically insignificant, as indicated by the t statistics and the p-values.

In our regressions, we measure monetary policy shocks (MP_t) by the exogenous component of M2 growth estimated by Chen et al. (2018) using a regime-switching approach. Based on China's institutional features, Chen et al. (2018) forcefully argue that quantity-based monetary policy is an important characterization of China's monetary system. This quantity-based measure of the monetary policy shock is also consistent with our theoretical model in which monetary policy controls the RR ratio. Furthermore, the exogenous component of M2 growth is orthogonal to other policy instruments, including the RR ratio, the repo rates, and the Shibor rates, suggesting that it captures exogenous shocks to China's monetary policy.[16]

[16]See Table S.3.1 in the Online Appendix S.3.

Table 2. Comparison of loan characteristics for high-risk and low-risk groups before 2013

Variables	(1) Low-risk group	(2) High-risk group	(3) Mean difference	(4) t-statistic	(5) p-value
SOE loan share	0.250	0.288	-0.038	-1.112	0.267
AAA&AA+ loan share	0.099	0.073	0.026	1.202	0.230
Small firm loan share	0.230	0.195	0.035	1.558	0.120
Average loan rate (%)	6.300	6.298	0.002	0.055	0.957
log(interest income)	16.828	16.868	-0.040	-0.255	0.799
log(loan amount)	19.601	19.641	-0.040	-0.253	0.801
Loan-to-firm asset ratio	0.138	0.129	0.008	0.386	0.700

Notes: Columns (1) and (2) report the average characteristics before 2013 of the low-risk group (i.e., bank branches with low NPL ratios) and the high-risk group (i.e., branches with high NPL ratios), respectively. Column (3) shows the differences in the average characteristics between these two groups. Columns (4) and (5) report the t-statistics and p-values from the t-test of the difference reported in Column (3). A branch is classified in the high-risk group if its average share of NPL in 2008-2012 exceeds the median. Otherwise, the branch is classified in the low-risk group. The loan amount, interest income, SOE loan amount share , high-rating (AAA or AA+) loan amount share, and small-firm loan share are calculated for each bank branch and averaged across time and across branches within each group. The average loan rate is calculated based on the loan rates weighted by loan volumes across branches within each group. The ratio of loan amount to firm's total asset is calculated for each loan deal, averaged across time for each branch and averaged across branches within each group.

Our theory predicts that, under Basel III, branches with higher NPL ratios before 2013 should be more aggressive in reducing risk-taking following a monetary policy easing. Thus, we should expect the coefficient on the triple interaction term $RiskH_j \times Post_y \times MP_t$ to be positive (i.e., $\beta > 0$).[17]

Our regressions include a vector of control variables (X_i) for the initial conditions facing firm i (i.e., the borrower of loan i). The control variables include firm size (measured by the log of total assets), age, leverage, the tangible asset ratio, and the returns on assets (ROA). We do not have data on these firm characteristics after 2013, since the

[17] Under the empirical specification (23), cross-sectional variations (measured by the branch-specific risk history $RiskH_j$) are crucial for identifying the effects of the Basel III regulations on bank risk-taking. Absent such cross-sectional variations, the effects of the regulatory changes ($Post_y$) and the interactions of regulations and monetary policy ($Post_y \times MP_t$) would be absorbed by the time fixed effects μ_t. Our theory does not have clear predictions about the signs of α and γ, the coefficients on the double interaction terms $RiskH_j \times Post_y$ and $RiskH_j \times MP_t$, respectively.

ASIF sample covers the period from 1998 to 2013. To capture potential time variations of firm characteristics, we follow Barrot (2016) and include the interactions between the initial conditions X_i with the year fixed effect μ_y.[18] The set of independent variables also includes branch locating city (or equivalently, city-level branch) fixed effect η_j, time (quarters) fixed effect μ_t, and firm locating province fixed effect ξ_p, industry fixed effect ζ_d. Finally, the term ϵ_{ijdpt} denotes the regression residual.[19]

Table 3 displays the summary statistics for the variables of interest in our analysis. The mean probability of high-rating lending (the $HighR$ dummy) is 4.2% with a standard deviation of about 0.2. The average share of high-risk branches (the $RiskH$ dummy) before 2013 is about 51.3%, with a standard deviation of 0.5. The monetary policy shock (MP) has a mean of zero and a standard deviation of 0.007.

TABLE 3. Summary statistics

Variables	Obs.	Mean	Std	Min	Median	Max
$HighR$	234,415	0.042	0.201	0.000	0.000	1.000
$RiskH$	322,961	0.513	0.500	0.000	1.000	1.000
MP	322,997	0.000	0.007	-0.017	0.001	0.027

III.3. **Empirical results.** We now discuss the empirical estimation results.

III.3.1. *Baseline estimation results.* Table 4 reports the estimation results from the baseline empirical model in Eq. (23). Consistent with theory, Column (1) shows that the estimated value of β (i.e., the coefficient on the triple interaction term) is positive and statistically significant. The positive value of β implies that, after the Basel III regulations were implemented, an expansionary monetary policy shock reduces risk-taking for high-risk branches relative to low-risk branches. In the full sample that includes the pre-Basel III periods, however, an expansionary monetary policy would increase risk-taking

[18]In our sample, the credit ratings of individual firms are very stable and rarely change over time (see Appendix B). It would be problematic to include controls for firm-year fixed effects, because they would be colinear with firm fixed effects. To mitigate concerns about potential effects from changes in loan demand conditions, we include controls for firm location fixed effects and also interactions of firm characteristics before 2013 with the year dummy. In Appendix C, following Degryse et al. (2019), we further control for demand factors by including firm size × location × industry × year-quarter fixed effects. In Section III.5, we present an alternative empirical specification that allows us to include firm-year-quarter fixed effects, which explicitly controls for demand-side effects.

[19]In the empirical specification (23), the effects of the linear term $RiskH_j$ are captured by the branch fixed effect η_j and the effects of the terms MP_t, $Post_y$, and $MP_t \times Post_y$ are captured by the time (year-quarter) fixed effect μ_t.

of high-risk branches, as indicated by the significantly negative estimates of γ (i.e., the coefficient on the double interaction term $RiskH_j \times MP_t$). We obtain similar estimation results when we further control for firm location fixed effects to capture demand-side factors (see Column (2) of the table).

The point estimate of $\beta = 0.848$ implies that, in the post-2013 period, a one-standard-deviation positive shock to monetary policy (i.e., and increase in MP of 0.7%) would raise the probability of lending to firms with high credit ratings by $0.848 \times 0.7\% = 0.59\%$, an increase of about 14% relative to the mean (the sample mean of the share of high-rating loans is 4.2%). Thus, the estimated effects of monetary policy shock on bank risk-taking under Basel III are both statistically significant and economically important.

III.3.2. *Parallel trends.* Our difference-in-difference identification assumes that the risk-taking responses to a monetary policy shock of the high-risk branches (the treated group) and those of the low-risk branches (the control group) followed parallel trends in the pre-Basel III periods, but their responses diverged after the new regulations were put in place.

To examine the validity of our parallel trends identification assumption, we estimate the dynamic impact of the response of risk-taking to a monetary policy shock for the treated group (β), by replacing the variable $Post_y$ with a series of time (year) dummies. We estimate the coefficients for the years before the new regulations (<2011 and 2011), the year when the regulation was implemented (2013), and the years after the regulation shock (>2013), all relative to the reference year of 2012.[20]

Figure 2 shows the point estimates of β for each sub-period, along with the 90% confidence bands. The figure shows that, before 2013, the estimated values of β are not significantly different from zero, implying that the risk-taking responses of the treated group to a monetary policy shock were not significantly different from those of the control group. In comparison, after 2013, the estimated values of β turned positive and statistically significant at the 90% confidence level, implying significant reductions in risk-taking of the treated group relative to the control group. These results validate our parallel trends identification assumption.

III.4. **Bank-level evidence.** To identify the effects of monetary policy shocks on bank risk-taking, we have used loan-level data from a single bank and exploited cross-sectional variations in lending behaviors across individual branches. One concern with this approach is that the CAR regulations are applied to the bank-level consolidated balance sheet, not directly to the branch level. As we have argued, branches can still respond

[20]For a similar approach to testing the validity of the parallel trends assumption, see Barrot (2016).

TABLE 4. Effects of monetary policy on bank risk-taking under capital regulations

	(1) $HighR$	(2) $HighR$
$RiskH_j \times MP_t \times Post_y$	0.836**	0.848**
	(0.383)	(0.378)
$RiskH_j \times MP_t$	-0.661**	-0.680**
	(0.317)	(0.316)
$RiskH_j \times Post_y$	0.00779	0.00665
	(0.00479)	(0.00451)
Initial controls × year FE	yes	yes
Branch FE	yes	yes
Year-quarter FE	yes	yes
Industry FE	yes	yes
Firm location FE	no	yes
Observations	206,738	206,738
R^2	0.199	0.230

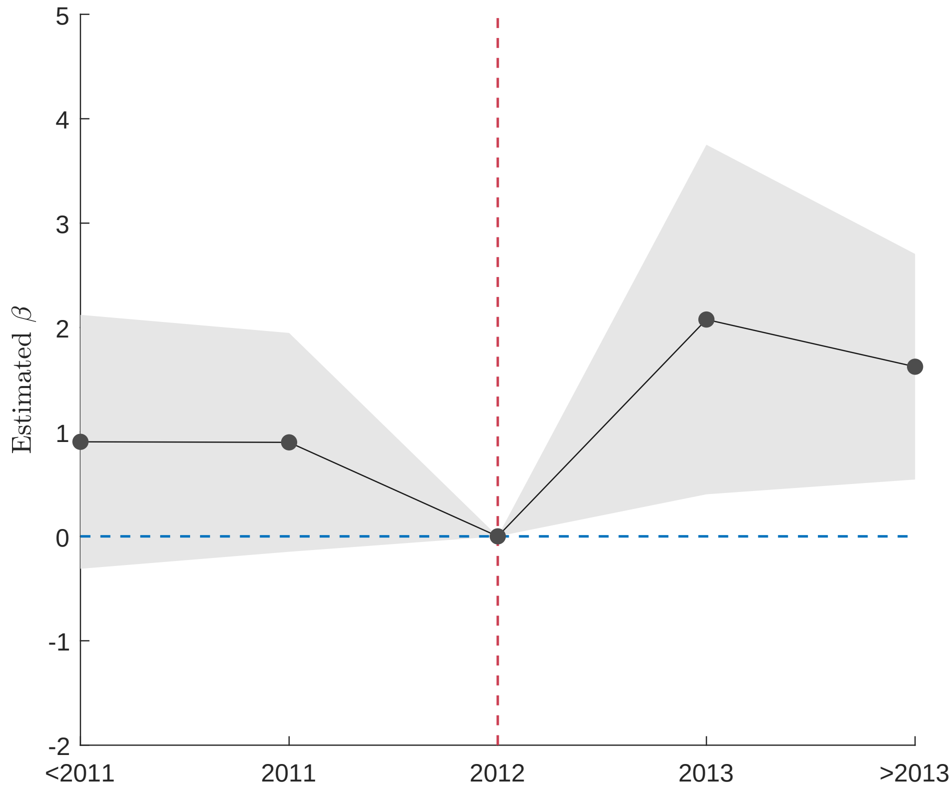
Notes: This table reports the estimation results in the baseline model. $HighR$ is a dummy variable that is equal to 1 if the rating of the loan is AA+ or AAA and zero otherwise. The monetary policy shock (MP_t) is constructed using the approach in Chen et al. (2018). Column (1) includes controls for branch fixed effects, industry fixed effects, year-quarter fixed effects, and average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. Column (2) includes additional controls for firm location (province) fixed effects. The numbers in parentheses indicate robust standard errors clustered at the branch level. The statistical significance levels are indicated by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

to regulation changes by adjusting the risk weights on their loans to meet the target of risk-weighted assets set by the bank headquarters. However, they cannot directly influence the bank-level capitalization. Our findings, however, are consistent with bank-level evidence.

To show this, we estimate the relation between risk-taking and monetary policy using data from 12 systemically important banks that are publicly listed in China.[21] Basel III raised the CAR ratio for all those large banks. However, only six of them implemented

[21]There were 13 systemically important banks classified by the China Banking Regulatory Commission in our sample from 2008Q1 to 2017Q4, including the Big Five banks, plus Ping An Bank, Shanghai Pudong Development Bank, China Minsheng Bank, China Merchants Bank, Industrial Bank, China

FIGURE 2. Parallel trends



Notes: The figure shows the estimated value of β for the years before 2011, 2011, 2013, and after 2013 from the empirical model, with 2012 as the reference year. The dots indicate the point estimates and the shaded gray areas indicate the 90% confidence bands. The treated group consists of high-risk bank branches with average NPL ratios above the median in the pre-2013 period. The control group consists of low-risk branches with pre-2013 average NPL ratios below the median. The coefficient β measures the differences in the risk-taking responses to a monetary policy shock between the treated and the control groups.

the IRB approach in 2013 (the Big-Five banks plus China Merchants Bank). We use those six banks that adopted the IRB approach as the treated group and the remaining six as the control group. In our bank-level dataset, we do not have loan-level information and thus we cannot directly measure a bank's portfolio risks based on the credit ratings of its loans. Following Laeven and Levine (2009), we use the Altman Z-score as a proxy for a bank's portfolio risks, and the Z-score is defined as a bank's return on assets plus the

Everbright Bank, China CITIC Bank, and China Guangfa Bank. Since China Guangfa Bank is not publicly listed, we do not have data from that bank.

capital asset ratio divided by the standard deviation of asset returns. A higher Z-score indicates lower risks.[22] We measure a bank's leverage using the growth rate of the ratio of total assets to bank equity. We regress the Z-score and the leverage growth on the triple interactions $Treat_k \times Post_y \times MP_t$, where $Treat_k$ is dummy indicator of whether a bank k is in the treated group. In the regressions, we include controls for the bank fixed effects, the year-quarter fixed effects, and the average bank characteristics (including loan-deposit ratio, nonperforming loan ratio, and the logarithms of total assets) in the years before 2013 (i.e., initial controls) interacted with the year-quarter fixed effects.

Table 5 shows the estimation results of the bank-level regressions. The positive estimated coefficients of the triple interaction term in both columns suggest that the banks that adopted the IRB approach (i.e., the treated banks) responded to an expansionary monetary policy shock in the post-2013 periods by reducing their portfolio risks (resulting in a higher Z-score) and increasing lending (with a higher leverage growth) relative to the control group. These effects are statistically significant at the 95% confidence level. Thus, the bank-level evidence is consistent with our loan-level evidence from the baseline estimation.

III.5. **Credit supply versus credit demand.** A potential concern of our baseline regression is that the responses of risk-taking behaviors to monetary policy shocks under Basel III might be driven by changes in loan demand of firms with different credit ratings, instead of changes in credit supply decisions.

To isolate the effects of the policy changes through the credit supply channel, we estimate an alternative empirical specification which allows us to control for time-varying borrower characteristics. We follow the approach of Khwaja and Mian (2008) and restrict our sample to those firms that borrow from multiple bank branches. We use loan prices or loan volumes as the dependent variable in the alternative specification.[23]

We use a similar DID identification approach to that in the baseline model, exploiting the differences in the loan prices or volumes offered by high-risk vs. low-risk bank branches. This effect is captured by the coefficient of the quadruple interaction term $RiskH_j \times HighR_{it} \times MP_t \times Post_y$, where the term $HighR_{it}$ is a dummy variable, which equals one if firm i's credit rating is AA+ or AAA and zero otherwise. The other

[22]The Altman Z-score measures a bank's insolvency risks, which depend on both leverage and asset risks. When we use the standard deviation of asset returns (instead of the Z-score) as a proxy for portfolio risks, we obtain similar results.

[23]One caveat of this alternative specification is that restricting the sample to those firms borrowing from multiple bank branches leads to a much smaller number of observations than our baseline sample (the number of observations in the restricted sample drops to about 11,000 from over 206,000 in the full sample). Thus, we do not use this specification as our baseline.

TABLE 5. Effects of monetary policy on bank risk-taking under capital regulations: Bank-level evidence

	(1)	(2)
	Z-score	*LevGrowth*
$Treat_k \times Post_y \times MP_t$	0.794**	5.005**
	(0.272)	(1.935)
$Treat_k \times MP_t$	-0.253	-1.637
	(0.178)	(1.581)
$Treat_k \times Post_y$	-0.00492	0.0124
	(0.00341)	(0.0182)
Initial controls × year FE	yes	yes
Year-quarter FE	yes	yes
Bank FE	yes	yes
Observations	459	441
R^2	0.671	0.571

Notes: This table reports the estimation results bank-level data. $Treat_k$ equals 1 if the bank implemented the IRB approach. The monetary policy shock is constructed using the approach in Chen et al. (2018). Both regressions include controls for bank fixed effects, year-quarter fixed effects, and the interactions of initial average bank characteristics (including loan-deposit ratio, nonperforming loan ratio, and the logarithms of total assets) in the years before 2013 (i.e., initial controls) with the year-quarter fixed effects. The Altman Z-score (logarithms) is measured by the bank's return on assets plus the capital asset ratio divided by the standard deviation of asset returns. *LevGrowth* is measured by the growth rate of total assets divided by equity. The numbers in parentheses indicate robust standard errors clustered at the bank level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

variables are defined in the baseline specification (23). We control for potentially time-varying demand factors by including a firm-year-quarter fixed effect in the regression.[24]

Table 6 shows that, controlling for firm-year-quarter fixed effects, an expansionary monetary policy shock in the post-2013 period leads to significant reductions in bank risk-taking: high-risk branches responded to the shock by reducing the loan interest rates and raising the loan volumes to firms with high credit ratings (i.e., the estimated coefficient of the quadruple interactions is negative for loan spread and positive for loan volumes). Since these effects are obtained after controlling for time-varying borrower

[24]In addition, we add Branch×Quarter FE and Branch×Post FE to capture the potential effect of the seasonality of the branch's behaviors (Murfin and Petersen, 2016), and the potential confounding effects of interest rate liberalization policies implemented around 2013 in China (Liu et al., 2021b).

TABLE 6. Effects of monetary policy on bank risk-taking under capital regulations: the credit supply channel

	(1)	(2)
	$LoanSpread$	$\log(Volume)$
$RiskH_j \times HighR_{it} \times MP_t \times Post_y$	-4.718***	116.5***
	(1.242)	(9.521)
$RiskH_j \times HighR_{it} \times Post_y$	-0.100***	-1.568***
	(0.00912)	(0.156)
$RiskH_j \times HighR_{it} \times MP_t$	0.0765	-3.917
	(0.724)	(19.72)
$RiskH_j \times MP_t \times Post_y$	0.737	-5.822
	(1.320)	(9.146)
$RiskH_j \times MP_t$	-0.105	0.359
	(1.214)	(4.977)
$RiskH_j \times HighR_{it}$	–	–
	–	–
Firm × Year-quarter FE	yes	yes
Branch × Post FE	yes	yes
Branch × Quarter FE	yes	yes
Observations	11,197	11,150
R^2	0.945	0.791

Notes: This table reports the estimation results using the sub-sample containing only those firms that borrow from two or more city-level bank branches. *LoanSpread* is the percentage deviations of the individual loan rate from the benchmark loan rate. The monetary policy shock is constructed using the approach in Chen et al. (2018). All Columns include controls for time-varying borrower characteristics captured by the firm × year-quarter fixed effects. In addition, we include controls for the Branch × Post fixed effects and Branch × quarter fixed effects. The numbers in the parentheses indicate robust standard errors triple clustered at the branch, firm, and year-quarter levels. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

characteristics, the decline in risk-taking primarily reflects the responses of lenders' credit supply decisions.

III.6. **Robustness.** Our main empirical results are robust to alternative measurements, specifications, and controls. In particular, the results remain valid when we consider (1) controlling for more loan demand factors in benchmark model,[25] (2) using the sub-sample with private firms only, (3) measuring monetary policy shocks based on an interest rate rule, (4) controlling for the effects of interest rate liberalization, (5) controlling for the effects of the deleveraging policy, (6) controlling for the effects of the anti-corruption campaign, (7) adding more controls in the baseline regressions, (8) using alternative measures of risk history, and (9) using local competition intensity as a source of cross-sectional variations (instead of using risk history). To conserve space, we report those results in Appendix C.

IV. Risk-taking and misallocation

The risk-weighting channel that we have identified has important implications for monetary policy transmission through credit misallocation. Under China's prevailing policy, SOEs have easier access to bank credit than private firms because, under government guarantees, SOEs are perceived as safer borrowers and SOE loans receive higher credit ratings. Thus, a bank can reduce portfolio risks following monetary policy easing by shifting lending to SOEs. However, SOEs have lower productivity on average than private firms (Hsieh and Klenow, 2009). Thus, shifting lending to SOEs can result in credit misallocation that reduces aggregate productivity. We now document evidence of such misallocation effects of monetary policy.

IV.1. **Ex-ante correlations between credit ratings and SOE loans.** Under government guarantees, SOE loans are considered safe lending and receive high ex-ante credit ratings. In our sample, SOE loans account for the bulk of the high-rating loans. Specifically, for the highly rated loans (AA+ or AAA), SOE lending accounts for 20-30% in terms of the number of loans and 55-60% in terms of the amount of lending.[26]

The positive correlation between high-rating loans and SOE lending prevails when we control for time and location fixed effects and firm characteristics. Table 7 shows the regression of credit ratings measured by 12 discrete categories of ratings (from B to AAA) on a dummy indicator of SOE loans, controlling for time and branch fixed effects and potentially time-varying firm characteristics. The SOE dummy equals one if the loan is extended to an SOE firm and zero otherwise. Estimating the regression using

[25]Because we cannot control for firm times year-quarter fixed effects in our benchmark model, following Degryse et al. (2019), we further control for firm size $\times$ location $\times$ industry $\times$ year-quarter fixed effects to isolate credit supply effects.

[26]See Table D.1 in the appendix.

Table 7. Credit ratings and SOE loans

	(1)	(2)	(3)
Credit Rating	OLS	Ordered probit	Ordered probit
SOE	0.933***	0.854***	0.343***
	(0.251)	(0.00875)	(0.0164)
Initial controls × year FE	yes	no	yes
Branch FE	yes	no	yes
Year-quarter FE	yes	no	yes
Industry FE	yes	no	yes
Firm location FE	yes	no	yes
Observations	206,744	234,415	206,745
R^2	0.244	–	–

Notes: Column (1) reports the results in OLS estimation. Columns (2)-(3) report results in ordered probit estimation. Initial controls include the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013. The numbers in parentheses are robust standard errors clustered at firm level for OLS model, and robust standard errors for order probit model . The statistical significance is denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

either the OLS or the ordered probit approach leads to a positive correlation between credit ratings and SOE lending, and the correlation is significant at the 99% confidence level.

IV.2. **Effects of policy changes on SOE lending and credit allocation.** The positive relation between SOE loans and high credit ratings suggests that, under Basel III capital regulations, a bank can reduce portfolio risks in response to an expansionary monetary policy shock by shifting lending to SOE firms. We now examine the empirical relevance of this credit reallocation channel.

We re-estimate the baseline specification (23) with the dependent variable replaced by the SOE dummy. Column (1) in Table 8 reports the OLS estimation results. The estimated coefficient on the triple interaction term $RiskH_j \times MP_t \times Post_y$ is positive and significant at the 95% confidence level, indicating that a high-risk branch is more likely to increase lending to SOEs than a low-risk branch following a monetary policy expansion in the post-2013 period. This finding, combined with those from the baseline regressions, suggests that bank branches reduce risk-taking by shifting lending to SOE firms.

Under China's policy, SOEs have favorable credit access despite their lower average productivity. The policy could lead to SOE over-investment, resulting in a lower marginal product of capital (MPK) of SOEs than that of private firms. Increased lending to low-MPK firms would be another indicator of credit misallocation.

We investigate this possibility by estimating the baseline regression with the dependent variable replaced by a measure of initial firm-level MPK. Specifically, the dependent variable (denoted by $HighMPK$) is a dummy indicator that equals one if a firm's average product of capital (measured by the ratio of sales to fixed capital stock) in the pre-Basel III period (2010 to 2012) exceeds the median among all firms. The set of independent variables is the same as in the baseline.

Column (2) in Table 8 shows that the coefficient of $RiskH_j \times MP_t \times Post_y$ is significantly negative, indicating that the branches in the high-risk group are less likely to lend to high MPK firms following monetary easing in the post-2013 period. This finding again supports the hypothesis that, under the Basel III capital regulations, monetary policy easing can lead to credit misallocation in China.

To further identify the channel effects of SOE lending on credit misallocation, we follow Bertrand and Mullainathan (2001) to use a two-stage least-squares estimation approach. In the first-stage regression, we predict SOE lending using the same set of explanatory variables used in our baseline regressions (i.e., those reported in Column (3) of Table 8). This regression helps isolate the effects of monetary policy shocks on SOE lending by high-risk branches under the Basel III regulations, capturing the risk-taking effects of monetary policy shocks. In the second stage, we regress the high-MPK indicator on the predicted SOE lending from the first stage. The second-stage regression coefficient captures the effects of monetary policy easing on capital allocations through the risk-taking channel.[27]

We report the two-stage estimation results in Columns (3) and (4) of Table 8. In the first-stage regression (Column (3)), the coefficient on the triple interaction term ($RiskH_j \times MP_t \times Post_y$) is positive and significant at the 95% level, consistent with the baseline results reported in Column (1).[28] In the second stage, we regress $HighMPK$ on the predicted SOE from the first stage. As shown in Column (4), the coefficient is negative and significant at the 90% level. Thus, an increase in SOE lending caused by an expansionary monetary policy shock under the Basel III regulations is associated with less lending to high-MPK firms. These results suggest that SOE lending is an

[27]This two-stage approach is formally identically to an instrumental-variable estimation where policy shocks are used as instruments for SOE lending.

[28]The coefficient estimates and the sample size in the first stage are different from those reported in Column (1), because of limitations of the sample of MPK used in the second-stage regression.

TABLE 8. Effects of monetary policy on SOE lending and credit allocation under capital regulations

	(1)	(2)	(3)	(4)
	SOE	$HighMPK$	SOE	$HighMPK$
	OLS	OLS	First-stage	Second-stage
$RiskH_j \times MP_t \times Post_y$	0.676**	-1.426*	0.685**	
	(0.341)	(0.768)	(0.318)	
$RiskH_j \times Post_y$	0.00221	-0.00503	0.00058	
	(0.00410)	(0.0142)	(0.00411)	
$RiskH_j \times MP_t$	-0.195	0.179	-0.241	
	(0.231)	(0.576)	(0.230)	
$\widehat{SOE}_{ijt}$				-2.370*
				(1.346)
Initial controls × year FE	yes	yes	yes	yes
Branch FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Firm location FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Observations	285,360	254,528	254,528	254,528
R^2	0.370	0.284	–	–

Notes: This table reports the estimation results on SOEs and marginal product of capital. $HighMPK$ is a dummy, if the firm's average product of capital (APK) ratio from 2010 to 2012 is greater than the median. APK is measured by the sales to the fixed capital ratio and divided by the industry median. The monetary policy shock is constructed using the approach in Chen et al. (2018). All regressions include controls for branch fixed effects, firm location fixed effects, industry fixed effects, year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors clustered at the branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

empirically important channel through which monetary policy shocks can lead to credit misallocation.

In Appendix D, we present further evidence of the misallocation effects of monetary policy shocks under the Basel III capital regulations. There, we use MPK dispersion across firms as a dependent variable. Since the ASIF data are not available after 2013, we construct the MPK dispersion across firms within each province using the data for publicly listed firms. We also construct a measure of the dispersion of marginal product of labor (MPL) across those listed firms. We estimate an OLS, regressing the dispersion of MPK (or MPL) on the same set of explanatory variables as in our baseline. We find that, following an expansionary monetary policy shock, those provinces with high exposures to NPL in the pre-2013 period experienced an increase in MPK dispersion in the post-2013 period, with no significant effects observed for MPL dispersion. These results are in line with the evidence documented by Gopinath et al. (2017) using Spanish firm data, and they lend further support to our main finding that a monetary policy expansion can exacerbate credit misallocation under the Basel III capital regulations.

IV.3. **Ex-post performance of SOE loans.** Since SOEs have lower average productivity than private firms in China (Hsieh and Klenow, 2009), the ex-ante high credit ratings of SOE loans may simply reflect government guarantees and do not necessarily imply better ex-post performance of those loans.

Table 9 confirms that the ex post performance (measured by the non-performing loan ratio, or NPL) of SOE loans is not better than non-SOE loans after controlling for credit ratings. Without controls for credit ratings, an SOE loan is less likely to be nonperforming (Column (1)), consistent with the fact that SOE loans receive higher credit ratings than non-SOE loans. However, when we control for credit ratings (Column (2)), the ex post performance of SOE loans was worse than non-SOE loans, although the difference is statistically insignifcant.

IV.4. **Effects of policy changes on productivity.** The misallocation effects of monetary policy induced by regulatory policy changes that we have established using micro-level data may have macro consequences. In particular, if the misallocation effects are important, we should observe that monetary policy easing would reduce aggregate productivity in the post-2013 period. We now examine this possibility using province-level annual data.

We construct a measure of total factor productivity (TFP) at the province level using the approach of Brandt et al. (2013). We regress TFP growth on its own lag and the triple interactions $MP_y \times Post_y \times RiskH_p$, where $RiskH_p$ is an indicator of province-level

TABLE 9. Ex-post performance of SOE loans

	(1) NPL	(2) NPL
SOE	-0.00648**	0.00201
	(0.00312)	(0.00467)
Credit Rating		-0.0108***
		(0.000560)
Initial controls × year FE	yes	yes
Branch FE	yes	yes
Industry FE	yes	yes
Year-quarter FE	yes	yes
Firm location FE	yes	yes
Observations	285,366	206,744
R^2	0.037	0.094

Notes: This table reports the estimated ex-post performance of SOE loans and loans with high credit ratings. NPL is a dummy variable that is equal to one if the status of the loan at the due year is classified as "substandard," "doubtful," or "loss"; and it is zero otherwise. The definitions of SOE and Credit Rating are the same as those in Table 7. All models include controls for the branch fixed effects, firm location fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors clustered at the firm level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

risk history of bank branches located in a given province. The regression also controls for the year fixed effects and the province fixed effects. Table 10 shows the estimation results using OLS (Column (1)) and the generalized methods of moments (GMM) approach for dynamic panels (Column (2)).

A coherent pattern emerges from our estimation: in the post-2013 period, an expansionary monetary policy shock reduces TFP growth significantly, especially in provinces with high-risk bank branches. For example, focusing on the OLS results in Column (1), the estimated coefficients imply that a one-standard-deviation positive shock to monetary policy in the post-2013 period reduces provincial TFP growth by about 0.26 percentage

Table 10. Bank risk-taking and aggregate productivity

	(1)	(2)
	TFP growth	TFP growth
	OLS	GMM
$RiskH_p \times MP_y \times Post_y$	-0.9137**	-3.3188**
	(0.4436)	(1.4095)
$RiskH_p \times Post_y$	-0.0104*	-0.0419*
	(0.0057)	(0.0127)
$RiskH_p \times MP_y$	0.1631	0.7958*
	(0.2823)	(0.4279)
Lag of TFP growth	yes	yes
Province FE	yes	yes
Year FE	yes	yes
AR(1) & AR(2) p-value		0.036, 0.746
Hansen & Sargan p-value		0.860, 0.840
R^2	0.771	–
Observations	390	390

Notes: This table reports the estimation results for the effects of regulatory and monetary policy changes on province-level TFP growth using the OLS (Column (1)) and the dynamic-panel GMM approach (Column (2)). TFP is measured based on the approach in Brandt et al. (2013). The annual series of monetary policy shocks is a within-year average of the quarterly shocks used in the baseline empirical specification. $RiskH_p$ is a dummy variable, equal to 1 if the average value of $RiskH_j$ in province p is above the median. Both models include controls for the province fixed effects and the year fixed effects. The numbers in parentheses indicate standard errors. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

points.[29] Our finding here suggests that the new capital regulations, by raising the share of bank lending to SOEs, have contributed to a slowdown in aggregate productivity growth following expansionary monetary policy shocks.

[29] In our sample, the standard deviation of the monetary policy shock is about 0.28% (at the annual frequency). Thus, the point estimate of -0.914 for the term $MP_y \times Post_y \times RiskH_p$ implies a reduction in TFP growth of $0.914 \times 0.28\% \approx 0.26\%$.

V. Conclusion

We present robust evidence that the implementation of Basel III regulations in 2013 has significantly changed Chinese banks' risk-taking responses to monetary policy shocks through a risk-weighting channel. Under the Basel III capital regulations, banks respond to an expansionary monetary policy shocks by increasing the share of lending to high credit-rating firms, reducing the portfolio risks. These effects are both statistically significant and economically important. Our estimation suggests that a one-standard-deviation increase in the exogenous component of M2 growth raises the probability of lending to firms with high credit ratings by up to 14% after the new regulations were put in place in 2013.

The risk-taking responses to monetary policy shocks have important implications for credit misallocation. Under China's prevailing policy that favors SOE credit access, banks can reduce their loan risk by shifting lending to SOEs. However, SOEs have lower average productivity than private firms. Thus, increasing lending to SOEs leads to credit misallocation that reduces aggregate productivity. Our evidence supports this misallocation channel of monetary policy transmission.

Although our data are from China, the general implications of our findings for the interconnection between monetary policy, bank risk-taking, and credit misallocation are not specific to that country. Our evidence suggests that changes in capital regulations that increase the sensitivity of risk-weighting help reduce bank risk-taking following monetary policy expansions. However, in the presence of other distortions, such as industrial policies that favor some inefficient firms (e.g., SOEs in China), banks reduce risk-taking by increasing lending to those favored firms, creating capital misallocation that depresses aggregate productivity. The trade-off between bank risk-taking and credit misallocation identified in our study is likely to play an important role in designing optimal macroeconomic stabilization policies.

Appendices

Appendix A. Basel III implementation and changes in China's bank capital regulations

In June 2012, the China Banking Regulatory Commission (CBRC) issued the "Capital Rules for Commercial Banks (Provisional)" (or *Capital Rules*), formally announcing the implementation of the Basel III capital regulations in China for all 511 commercial banks in the country, effective on January 1, 2013. The new policy specified in the *Capital Rules* requires commercial banks to have a CAR of at least 8%, where the CAR is calculated as the ratio of bank capital net of deductions to risk-weighted assets. Commercial banks are required to hold an additional capital conservation buffer equivalent to 2.5% of risk-weighted assets, bringing the minimum CAR requirement to 10.5%. For systemically important banks, the minimum CAR was raised further to 11.5%. Banks should also hold a countercyclical capital buffer, the size of which varies between 0 and 2.5% of risk-weighted assets.[1]

The implementation of Basel III regulations in China not only raised the minimum CAR but also changed the approach to measuring bank assets for calculating the CAR. Before 2013, bank assets were calculated based on the regulatory weighting (RW) approach. The RW approach assigns ad hoc risk weights to different categories of loans, independent of credit risk.[2] Under the new regulatory regime after 2013, a commercial bank is allowed (and often encouraged) to calculate its assets using the internal ratings based (IRB) approach.[3] The IRB approach assigns risk weights to loans based on their credit risk. A loan with a higher credit rating would receive a lower risk weight.[4] All else being equal, SOE loans receive higher credit ratings than private firms. Thus, the IRB approach assigns a lower risk weight to SOE loans.

The introduction of the IRB approach to calculating risk-weighted assets has changed the effective CAR. Since 2013, the Big Five commercial banks started to regularly release

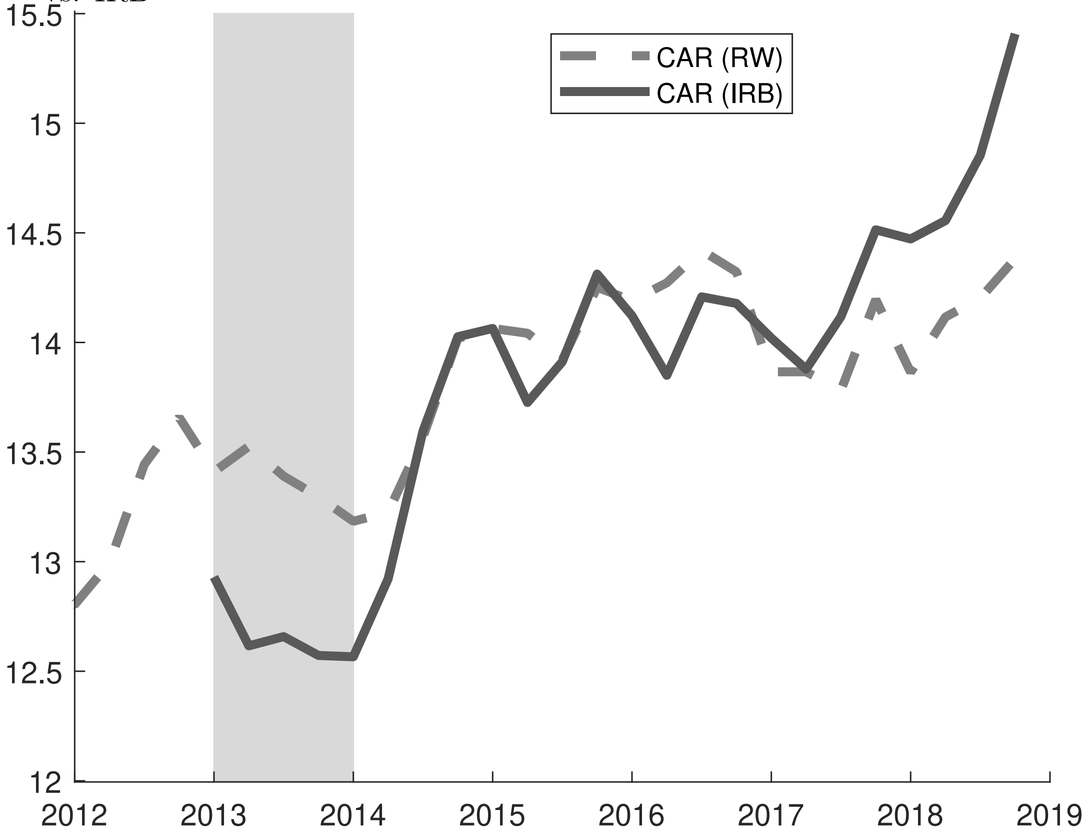
[1]For more details about the new regulation, see
http://www.cbrc.gov.cn/EngdocView.do?docID=86EC2D338BB24111B3AC5D7C5C4F1B28.

[2]For example, the risk weight on corporate loans is 100%, regardless of the firm's credit rating.

[3]The CBRC encouraged commercial banks to adopt the IRB approach when evaluating risk-weighted assets. According to the regulation, a commercial bank can apply to the CBRC to adopt the IRB approach. The minimal requirement for the applicant bank is that the coverage of the IRB approach should be no less than 50% of the total risk-weighted assets, and this ratio must reach 80% within three years.

[4]For example, Article 76 of the *Capital Rules* specifies that the risk weights for non-retail exposures not in default are calculated based on the probability of default, loss at a given default, exposure at default, and the correlation and maturity of each individual exposure.

FIGURE A.1. Average capital adequacy ratios for the Big Five banks: RW vs. IRB



Notes: This figure presents the quarterly average CAR of the Big Five commercial banks under both the traditional regulatory weighting approach (RW, dashed line) and the new Internal Ratings Based approach (IRB, solid line). The shaded area indicates the period from 2013Q1 to 2014Q1 when the new regulation was enacted, but the banks still used the RW approach to assess risk-weighted assets. Data source: WIND.

an annual report of their CARs, with different definitions: one based on the pre-2013 RW approach, and the other based on the new IRB approach.

Figure A.1 shows the quarterly average value of the RW-based CAR (dashed line) and the IRB-based CAR (solid line) for the Big Five banks. In 2013, when the CBRC began to implement the Basel III regulations, the IRB-based CAR was substantially below the traditional RW-based CAR (with the period highlighted by the shadow area). The IRB-based CAR caught up quickly with the RW-based CAR by mid-2014. Since 2017, the IRB-based CAR has exceeded the traditional RW-based CAR. The time variation of the gap between the IRB-based and RW-based CARs reflects (at least partly) the banks' risk-weight adjustments in their asset allocations following the implementation of Basel III regulations.

Appendix B. Stability of credit ratings

In our sample, a firm's credit rating rarely changes over time, as shown in Table B.1.

Table B.1. Number of Firms with Time-varying Credit Ratings

Year	$Rating_t = Rating_{t-1}$	$Rating_t \neq Rating_{t-1}$
2009	5,674	6
2010	6,565	2
2011	8,046	4
2012	9,427	4
2013	9,621	2
2014	8,940	1
2015	8,029	3
2016	6,932	2
2017	6,105	0

Appendix C. Further robustness checks

Our main empirical results are robust to alternative measurements, specifications, and controls.

Controlling for more loan demand factors. To further control for potential effects of loan demand factors, we add more control variables in the baseline regression. Table C.1 shows the estimation results with successively more stringent controls of demand factors. Column (1) shows the baseline regression that includes firm location fixed effects. Column (2) includes firm location × year-quarter fixed effects. Column (3) includes industry × firm location× year-quarter fixed effects. Column (4) includes firm size × industry × firm location × year-quarter fixed effects. In each case, we obtain a positive and significant estimate of the coefficients of the triple interaction term $RiskH_j \times MP_t \times Post_y$. Thus, the baseline results are robust to including these demand controls.

TABLE C.1. Effects of monetary policy on bank risk-taking under capital regulations: Additinoal controls for demand factors

	(1)	(2)	(3)	(4)
	$HighR$	$HighR$	$HighR$	$HighR$
$RiskH_j \times MP_t \times Post_y$	0.848**	0.616*	0.512*	0.504*
	(0.378)	(0.351)	(0.305)	(0.303)
$RiskH_j \times MP_t$	-0.679**	-0.468	-0.273	-0.275
	(0.316)	(0.297)	(0.235)	(0.241)
$RiskH_j \times Post_y$	0.00665	0.00592	0.00451	0.00496*
	(0.00451)	(0.00395)	(0.00288)	(0.00271)
Initial controls × year FE	yes	yes	yes	yes
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	–	–	–
Firm location FE	yes	–	–	–
Industry FE	yes	yes	–	–
Firm location × Year-quarter FE		yes	–	–
Industry × Firm location× Year-quarter FE			yes	–
Firm size × Industry × Firm location × Year-quarter FE				yes
Observations	206,738	206,717	202,743	202,743
R^2	0.230	0.250	0.472	0.489

Notes: This table reports the estimation results in the baseline model. $HighR$ equals 1 if the loan rating is AA+ or AAA and zero otherwise. The monetary policy shock is constructed using the approach in Chen et al. (2018). All of the models include controls for branch fixed effects and the average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 (i.e., initial controls) interacted with year fixed effects. Column (1) shows the baseline regression that includes firm location fixed effects. Column (2) includes firm location × year-quarter fixed effects. Column (3) includes industry × firm location× year-quarter fixed effects. Column (4) includes firm size × industry × firm location × year-quarter fixed effects. The numbers in parentheses indicate robust standard errors clustered at the branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

Estimation with POE subsample only. To ensure our results are not driven by SOEs, we re-estimate the baseline specification using the sub-sample with private firms. As shown in Table C.2, the baseline results obtained from the full sample (Column (1)) are robust to the exclusion of SOEs from the sample (Column (2)), indicating that our main findings are not driven by SOEs.

TABLE C.2. Effects of monetary policy on bank risk-taking under capital regulations: Excluding SOE firms

	(1)	(2)
	$HighR$	$HighR$
	Full Sample	Excluding SOEs
$RiskH_j \times MP_t \times Post_y$	0.848**	0.831**
	(0.378)	(0.359)
$RiskH_j \times Post_y$	0.00665	0.00607
	(0.00451)	(0.00443)
$RiskH_j \times MP_t$	-0.679**	-0.684**
	(0.316)	(0.308)
Initial controls × year FE	yes	yes
Industry FE	yes	yes
Firm location FE	yes	yes
Branch FE	yes	yes
Observations	206,738	197,661
R^2	0.230	0.204

Notes: This table reports the estimation results in the baseline model (Column (1)) and the regression using the sample that excludes SOEs (Column (2)). $HighR$ equals 1 if the loan rating is AA+ or AAA and zero otherwise. The monetary policy shock is constructed using the approach in Chen et al. (2018). Both regressions include controls for branch fixed effects, the average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 (i.e., initial controls) interacted with year fixed effects, industry fixed effects, firm location fixed effects, and branch fixed effects. The numbers in parentheses indicate robust standard errors clustered at the branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

Measuring monetary policy shocks based on an interest rate rule. In the baseline empirical model, we use a quantity-based measure of monetary policy shocks. In recent years, monetary policy has gradually shifted toward market-based policy, with interest rates used as a policy instrument (Fernald et al., 2014).[5] To check the robustness of our results, We estimate the baseline empirical specification (23), with the monetary policy shock measured by the Taylor rule residuals estimated from the Taylor-rule

[5]Chang et al. (2015) discuss the implications of interest rate rules for macroeconomic stability and welfare in a dynamic stochastic general equilibrium (DSGE) model of China. In practice, China's monetary policy is more complex, including both quantity instruments and interest rates (Girardin et al., 2017).

specification

$$i_t = \rho i_{t-1} + \phi^{\pi} \pi_{t-1} + \phi^{y} \hat{y}_{t-1} + \varepsilon_t. \tag{C.1}$$

Here, i_t denotes the nominal interest rate, π_{t-1} and $\hat{y}_{t-1}$ denote, respectively, the inflation rate and the output gap in period $t-1$, ε_t is a residual. We consider both the 30-day Shanghai Interbank Offered Rate (Shibor) or the 30-day Interbank Pledged Repo Rate (Repo) as a proxy for the policy rate. We measure inflation using 12-month changes in China's consumer price index (CPI). The output gap is measured by the log-deviations of real GDP from its Hodrick-Prescott (HP) trend. The regression residuals correspond to the measure of monetary policy shocks under the Taylor rule. A negative value of the shock implies an easing of monetary policy. This price-based monetary policy shock is moderately correlated with the quantity-based shock, with a correlation of -0.46.

The results are displayed in Table C.3, using either the Shibor (Column (1)) or the Repo rate (Column (2)) as a measure of the policy interest rate. In both cases, we obtain a negative and significant estimate of the coefficient on the triple interaction term, indicating that, under Basel III, monetary policy easing (i.e., a decline in the policy interest rate) reduces bank risk-taking for high-NPL branches. Thus, our baseline results are robust to these interest-rate-based measures of monetary policy shocks.

Controlling for the impact of interest rate liberalization. China has traditionally maintained interest rate controls. Under the interest rate control regime, the PBOC sets the benchmark deposit interest rate and loan interest rate and allows banks to offer a range of interest rates that are within a narrow band of those benchmark rates. In 2013, the PBOC relaxed controls over bank lending rates. Subsequently, in 2015, the PBOC also widened the range of the deposit rates that banks can offer. These interest rate liberalization policies might confound the effects of the Basel III regulatory regime.

To address this concern, we include in our baseline regression additional controls for the effects of interest rate fluctuations. In particular, we include the interaction terms $RiskH_j \times LoanRateGap_t$ and $RiskH_j \times MP_t \times LoanRateGap_t$ as additional control variables, where $LoanRateGap_t$ measures the percentage deviation of the *average* lending interest rate across all loans from the benchmark lending rate in quarter t. A larger deviation from the benchmark indicates more flexibility for the bank to set lending rates. Thus, including this variable in the regression helps capture the effects of interest rate liberalization on the risk-taking channel of monetary policy.

Table C.4 displays the estimation results. After controlling for the effects of interest rate liberalization, we still obtain a positive and significant coefficient on the triple interaction term $RiskH_j \times MP_t \times Post_y$, suggesting that our baseline results are robust and they are not driven by other reforms such as interest rate liberalization.

TABLE C.3. Effects of monetary policy on bank risk-taking under capital regulations: Interest rate shocks

	(1) $HighR$	(2) $HighR$
$RiskH_j \times MP_t^{Shibor} \times Post_y$	-0.477*	
	(0.271)	
$RiskH_j \times MP_t^{Shibor}$	0.565**	
	(0.239)	
$RiskH_j \times MP_t^{Repo} \times Post_y$		-0.422*
		(0.250)
$RiskH_j \times MP_t^{Repo}$		0.510**
		(0.222)
$RiskH_j \times Post_y$	0.00990***	0.00980***
	(0.00126)	(0.00127)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls × year FE	yes	yes
Observations	223,014	223,014
R^2	0.126	0.126

Notes: This table reports the estimation results based on price-based monetary policy shocks. $HighR$ is equal to 1 if and only if the rating of the loan is AA+ or AAA.The price-based monetary policy shock is constructed using the Taylor Rule. We employ two interest rates as proxies for the policy rate, including 30-day Shanghai Interbank Offered Rate (Shibor) and 30-day Interbank Pledged Repo Rate (Repo). The Taylor rule equation takes the form of $i_t = \rho i_{t-1} + \phi^{\pi}\pi_{t-1} + \phi^{y}\hat{y}_{t-1} + \varepsilon_t$, where t represents one quarter, i_t is the interest rate, and π_t and y_t are the inflation rate and the output gap, respectively. The output gap is measured by the log-deviation of real GDP from its HP trend. The residual ε is a price-based measure of monetary policy shock. The estimation includes controls for the branch fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

Table C.4. Effects of monetary policy on bank risk-taking under capital regulations: Controlling for the impact of interest rate liberalization

	(1)
	$HighR$
$RiskH_j \times MP_t \times Post_y$	1.082**
	(0.507)
$RiskH_j \times Post_y$	0.00765*
	(0.00420)
$RiskH_j \times MP_t$	-0.324
	(0.551)
$RiskH_j \times MP_t \times LoanRateGap_{t-1}$	-5.139
	(6.479)
$RiskH_j \times LoanRateGap_{t-1}$	-0.00476
	(0.0332)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial controls × year FE	yes
Observations	193,263
R^2	0.218

Notes: The monetary policy shock is constructed using the approach in Chen et al. (2018). $LoanRateGap_t$ is the deviation of the average lending rate of all loans from the benchmark lending rate in quarter t. The absolute size of $LoanRateGap_t$ captures the effectiveness of interest rate liberalization on lending interest rates. Both models include controls for the branch fixed effects, industry fixed effects, firm location fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors clustered at branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

Effects of deleveraging policy: A placebo test. The Chinese government responded to the 2008-09 global financial crisis by implementing a large-scale fiscal stimulus (equivalent to about 12% of GDP). The fiscal stimulus helped cushion the downturn during the crisis period, but it has also led to a surge in leverage and over-investment, particularly in those sectors with a high share of SOEs (Cong et al., 2019). In December 2015, the Chinese government implemented a deleveraging policy, aiming to reduce the leverage in the over-capacity industries. It is possible that the deleveraging policy might have played a role in driving the observed relation between bank risk-taking and monetary policy shocks.

To examine this possibility, we conduct a placebo test using China's deleveraging policy. We define a dummy variable, $DeLev_y$, which is equal to one if the year is 2016 or after, and zero otherwise. In the placebo test, we estimate the baseline empirical model (23), replacing the variable $Post_y$ in the baseline model with $DeLev_y$. Table C.5 shows the estimation results. Unlike the banking regulation policy changes under Basel III, the deleveraging policy did not change the bank risk-taking behaviors following monetary policy shocks.

Controlling for the effects of the anti-corruption campaign. In late 2012, China started a sweeping anti-corruption campaign that has brought down numerous officials at all levels of the government. The timing of the anti-corruption campaign coincides with the implementation of Basel III, potentially confounding the effects of the regulatory changes. For example, banks might want to shift lending to SOEs from private firms to avoid potential anti-corruption investigations. To address this concern, we add controls in our regressions to capture the effects of the anti-corruption campaign on bank lending behavior. We measure the local impact of the campaign by a dummy variable (denoted by $AntiCorrup_j$) that is equal to one if, in the province where city j is located, at least one province-level official has been imprisoned for corruption since 2012.

Table C.6 shows the OLS regression results, controlling for the effects of the anti-corruption campaign. The estimated coefficient on the interaction term $AntiCorrup_j \times Post_y$ is positive and significant, confirming that bank branches located in areas hit by the anti-corruption campaign are more likely to lend to firms with high credit ratings in the post-2013 period, possibly due to the fear of being investigated.

However, adding controls for the anti-corruption effects does not affect our main empirical finding. As shown in Table C.6, in the post-2013 period, high-risk branches are more likely to lend to highly rated firms following an expansionary monetary policy shock.

Table C.5. Deleveraging policy and the effects of monetary policy on bank risk-taking: A placebo test

	(1)
	$HighR$
$RiskH_j \times MP_t \times Delev_y$	-0.956
	(1.025)
$RiskH_j \times Delev_y$	0.00156
	(0.00542)
$RiskH_j \times MP_t$	-0.314
	(0.201)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial control × year FE	yes
R^2	0.230
Observations	206,738

Notes: $DeLev_y = 1$ if $y \geq 2016$ and 0 otherwise. All other variables have the same definitions as those in the baseline estimations. The regression includes controls for the branch fixed effects, the industry fixed effects, firm location fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors clustered at branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

Additional controls. Our baseline regression includes controls for branch fixed effects, year-quarter fixed effects, industry fixed effects, firm location fixed effects, and interactions between firms' initial characteristics and the year fixed effects. To examine the robustness of our results, we now consider three additional controls.

The first control variable that we include is the interaction between bank branches' initial profits (denoted by $InitProfit_j$) and the year fixed effects, where the initial profit of branch j is measured by its net interest income in the first year when the branch is

TABLE C.6. Effects of monetary policy on bank risk-taking under capital regulations: Controlling for effects of anti-corruption campaigns

	(1)
	$HighR_{i,j,t}$
$RiskH_j \times MP_t \times Post_y$	0.854**
	(0.384)
$RiskH_j \times Post_y$	0.00645
	(0.00432)
$RiskH_j \times MP_t$	-0.683**
	(0.322)
$AntiCorrup_j \times Post_y$	0.0109**
	(0.00458)
$AntiCorrup_j \times MP_t$	0.318
	(0.338)
$AntiCorrup_j \times MP_t \times Post_y$	-0.211
	(0.399)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial controls × year FE	yes
Observations	206,738
R^2	0.230

Notes: $AntiCorrup_j$ is a dummy variable, which is equal to one if the bank branch is located in a city within a province where at least one province-level official was investigated for corruption in 2012. The regression includes controls for the branch fixed effects, firm location fixed effects, industry fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses show the robust standard errors clustered at branch level. The levels of statistical significance are denoted by asterisks: *** for p < 0.01, ** for p < 0.05, and * for p < 0.1.

observed in our sample. Including this control helps rule out the possibility that the banking regulation may change a branch's lending behavior through affecting its profit.[6]

The second additional control variable that we include in the regression is the interaction between the initial share of SOE loans (denoted by $InitSOE_j$) and the year fixed effects, where the initial SOE share is measured by the average share of SOE loans issued by bank branch j before 2013. This control variable addresses the possibility that issuing more SOE loans may lead to a higher NPL ratio for a branch, such that the independent variable $RiskH_j$ can be potentially endogenous.

Table C.7 shows the regression results with these two additional controls (adding one at a time). Our main findings in the baseline estimation remain robust.

Alternative definition of risk history. In the baseline regressions, we use the pre-2013 average NPL ratio to measure the risk history of each branch. Since NPL is an ex post measure which could be affected by local economic conditions, we consider an alternative measure of risk history based on ex ante credit ratings of loans. In particular, we measure a branch's risk history by (the negative of) the average credit ratings of its loans during the pre-2013 period. Under this alternative measure, a branch is classified as a high-risk branch if its loans had low average credit ratings in the pre-2013 period. The main results are robust to using this alternative definition of risk history, as shown in Table C.8.

Alternative measures of cross-sectional variations. In our baseline regression, we identify the risk-weighting channel by exploiting the cross-sectional variations in the risk history of bank branches. The estimation results are robust when we use cross-sectional variations in the local loan market competition intensity to identify the risk-weighting channel.

To provide a theoretical underpinning for this alternative identification approach, we extend the baseline theoretical model to incorporate local banking competition.[7] The model predicts that, following an easing of monetary policy, a bank branch facing more local competition would raise leverage more aggressively and, under the CAR constraints, it would also reduce risk-taking more aggressively. Increasing the risk-weighting sensitivity would further amplify those effects.[8]

[6]The bank headquarters may set a requirement on a branch's profit, which might influence the branch's lending behaviors in response to changes in banking regulations.

[7]To conserve space, we present the details of the model in the online appendix.

[8]The literature highlights two other channels through which bank competition can affect risk-taking. More intensive competition reduces loan interest rates, such that borrowers would choose safer projects, reducing risk (Boyd and Nicoló, 2005). However, increased competition could also reduce a bank's

TABLE C.7. Effects of monetary policy on bank risk-taking under capital regulations: Additional controls

	(1)	(2)
	$HighR_{i,j,t}$	$HighR_{i,j,t}$
$RiskH_j \times MP_t \times Post_y$	0.850**	0.848**
	(0.377)	(0.376)
$RiskH_j \times Post_y$	0.00648	0.00636
	(0.00437)	(0.00436)
$RiskH_j \times MP_t$	-0.679**	-0.678**
	(0.315)	(0.314)
$InitProfit_j \times$ year FE	yes	yes
$InitSOE_j \times$ year FE	no	yes
Branch FE	yes	yes
Year-quarter FE	yes	yes
Industry FE	yes	yes
Firm location FE	yes	yes
Initial controls $\times$ year FE	yes	yes
Observations	206,738	206,738
R^2	0.230	0.230

Notes: All Columns report the results in OLS estimations. The $InitProfit_j$ is measured by the interest income of bank branch j in the first year that the branch was observed in our sample. The variable $InitSOE_j$ is measured by the average share of SOE loans issued by bank branch j before 2013. All other variables have the same definitions as those in the baseline estimations. All models include controls for the branch fixed effects, the industry fixed effects, firm location fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors clustered at branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

profits and its franchise value and therefore exacerbate the incentive for risk-shifting, resulting in a nonlinear relation between competition and risk-taking (Martinez-Miera and Repullo, 2010). For empirical evidence of this nonlinear relation, see, for example, Jiménez et al. (2013).

TABLE C.8. Effects of monetary policy on bank risk-taking under capital regulations: Alternative measure of risk history

	(1)
	$HighR_{i,j,t}$
$RiskH2_j \times MP_t \times Post_y$	0.261**
	(0.131)
$RiskH2_j \times Post_y$	0.00273
	(0.107)
$RiskH2_j \times MP_t$	-0.276**
	(0.107)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial controls × year FE	yes
Observations	206,738
R^2	0.230

Notes: Risk history ($RishH2_j$) is measured by the negative of the average credit ratings of the loans extended by bank branch j from 2008 to 2012. All models include controls for the branch fixed effects, industry fixed effects, firm location fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. The numbers in parentheses indicate robust standard errors clustered at branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

In our regression, we replace the risk-history indicator ($RiskH_j$) with an indicator of local market competition, which is measured by (the logarithm of) the number of subbranches of other commercial banks within a 5-kilometer radius around a given subbranch k of the bank in our sample (denoted as $LocalComp_k$). The presence of a larger number of competing subbranches in the same vicinity (i.e., a larger value of $LocalComp_k$) indicates more intense local competition facing the subbranch k.[9]

[9] Our distance-based measure of local market competition is supported by empirical evidence (Degryse and Ongena, 2005). We measure local competition based on the number of competitors at the subbranch level in a given city because each city has only one main branch of the bank in our sample and there are

TABLE C.9. Effects of monetary policy on bank risk-taking under capital regulations: Local competition

	$HighR$	$HighR$
$LocalComp_k \times MP_t \times Post_y$	0.522**	0.457**
	(0.223)	(0.199)
$LocalComp_k \times Post_y$	0.00243	0.00339
	(0.00307)	(0.00272)
$LocalComp_k \times MP_t$	-0.305*	-0.244*
	(0.170)	(0.147)
$LocalComp_k$	-0.00114	-0.00311
	(0.00395)	(0.00342)
Initial controls × year FE	yes	yes
Branch FE	yes	yes
Industry FE	yes	yes
Year-quarter FE	yes	yes
Firm location FE	no	yes
R^2	0.201	0.234
Observations	195,954	195,954

Notes: This table reports the estimation results based on an alternative cross-branch variation, $LocalComp_k$, which is the logarithm of the number of subbranches of other commercial banks within a 5 km radius around the subbranch k in our sample. The other variables are defined in the same way as in the baseline regression. All models include controls for the branch fixed effects, the industry fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. Column (2) additionally controls for firm location fixed effects. The numbers in parentheses indicate robust standard errors clustered at the branch level. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

Table C.9 reports the estimation results. Column (1) shows the OLS estimation results. The estimated coefficient on $LocalComp_k \times MP_t \times Post_y$ is significantly positive, consistent with the theory's predictions and also with our baseline results that, under Basel III, monetary policy easing reduces bank risk-taking.

relatively few competing main branches affiliated with other commercial banks in the same city, limiting the size of our sample.

Table D.1. Credit ratings and SOE loan share

Credit Rating	Number	SOE Share	Amount	SOE Share
AAA	4280	20.4%	223354	60.5%
AA+	6424	30.8%	294035	55.1%
AA	21357	21.7%	492607	52.4%
AA-	49473	7.9%	604074	31.6%
A+	50301	4.4%	372378	21.5%
A	24712	8.3%	236982	27.2%
A-	14803	2.7%	101295	14.4%
BBB+	13655	1.5%	83454	7.9%
BBB	9437	2.3%	64933	22%
BBB-	4779	0.8%	34362	2.4%
BB	9143	6.9%	90197	21.4%
B	55849	1.6%	407239	4.8%

Notes: The column "Amount" shows the total volume of loans in each credit rating category (in millions of yuans).

Appendix D. Additional evidence of misallocation effects of monetary policy through the risk-weighting channel

Credit ratings and SOE loan share. Table D.1 shows the SOE shares of loans with different credit ratings. SOE loans account for a large share of highly rated loans. In terms of the number of loans, over 50% of the highly rated loans (AA+ or AAA) were extended to SOE firms. In terms of the amount of loans, over 55% of the highly rated loans were extended to SOEs.

MPK dispersion as a measure of capital misallocation. In the literature, resource misallocations are often measured by the dispersion of marginal product of capital (MPK) [e.g., Hsieh and Klenow (2009)]. We follow the literature and use the MPK dispersion to measure capital misallocation. Since the firm-level characteristics in the ASIF database are not available after 2013, we construct the dispersion of MPK and also of marginal product of labor (MPL) within each province using the data from publicly listed firms. Table D.2 reports the estimation results. The estimated coefficient of the triple interaction term $RiskH_p \times MP_y \times Post_y$ in Column (1) is positive and significant, suggesting that, after the implementation of Basel III capital regulations, provinces with higher exposures to risky bank branches experienced larger increases in capital misallocation (measured by the MPK dispersion) in response to an expansionary monetary policy

TABLE D.2. Bank risk-taking and resource misallocation: MPK dispersion

	(1) MPK dispersion OLS	(2) MPL dispersion OLS
$RiskH_p \times MP_y \times Post_y$	9.3322*	7.4480
	(4.9169)	(4.7789)
$RiskH_p \times Post_y$	-0.0545	-0.0776
	(0.0579)	(0.0563)
$RiskH_p \times MP_y$	-7.9711**	-5.0035
	(4.0435)	(3.9300)
Province FE	yes	yes
Year FE	yes	yes
R^2	0.514	0.495
Observations	330	330

Notes: This table reports the estimated effects of regulatory and monetary policy changes on the dispersion of MPK (Column (1)) and on MPL (Column (2)). The dispersion of MPK is measured by the standard deviation of log(APK), where APK is the ratio of sales to fixed asset normalized by the industry median. Similarly, the dispersion of MPL is measured by the standard deviation of log(APL), where APL is the ratio of sales to employment normalized by the industry median. The calculations of APL and APK are based on the data of publicly listed Chinese firms. The yearly monetary policy shock is aggregated using quarterly shocks. $RiskH_p$ is a dummy that equals one if the average value of $RiskH_j$ in province p is above the median within a year. Both regressions include controls for the province fixed effects and the year fixed effects. The numbers in parentheses indicate standard errors. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

shock. In comparison, as Column (2) shows, the effects of the regulatory and monetary policy changes on the MPL dispersion are insignificant, suggesting that those policy changes are important mostly for the capital misallocations.

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Supplemental Appendices: For Online Publication

Appendix S.1. Proofs

This section provides some lemmas and proofs of the propositions in Section II.

Lemma 1 and the Proof.

Lemma 1. Under condition (11), there exists a unique $\sigma \in (0, \bar{\sigma})$ that maximizes the bank's expected profit. Furthermore, we have

$$\frac{\partial \sigma}{\partial \psi} < 0, \quad \frac{\partial \sigma}{\partial \rho} < 0. \tag{S.1.1}$$

Thus, the optimal project risk decreases with both the level of required capitalization (ψ) and the sensitivity of risk-weighting to portfolio risks (ρ).

Proof. With the uniform distribution of project returns, the marginal effect of the project risk on the bank's expected profits, (14), is

$$\begin{aligned}
\frac{\partial V/e}{\partial \sigma} &= \lambda(\sigma)\left[\frac{\partial E\left[R\left(\sigma\right)\right]}{\partial \sigma} + \frac{\partial}{\partial \sigma}\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))}\left(R^*\left(\lambda(\sigma)\right) - R\right)d\mathbf{F}(R)\right] \\
&= \lambda\left(\phi_1 - 2\phi_2\sigma\right) - \frac{\lambda}{\sigma}\left(\phi_1 - 2\phi_2\sigma - \frac{1}{2}\right)\left(R^* - \underline{R}\right) - \frac{\lambda}{2\sigma^2}\left(R^* - \underline{R}\right)^2 \\
&= \frac{\lambda}{\sigma}\left(\bar{R} - R^*\right)\left[\frac{\partial \bar{R}}{\partial \sigma} - \frac{1}{2\sigma}\left(\bar{R} - R^*\right)\right] > 0. \qquad \text{(S.1.2)}
\end{aligned}$$

The last inequality holds for $\sigma \in (0, \sigma^*)$ and $R^* > \underline{R}$. The marginal effect of leverage on the bank's expected profits, (15), is

$$\begin{aligned}
\frac{\partial V/e}{\partial \lambda} &= E\left[R\left(\sigma\right)\right] - r + \int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))}\left(R^*\left(\lambda(\sigma)\right) - R\right)d\mathbf{F}(R) \\
&+ \lambda\frac{\partial}{\partial \lambda}\left[\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))}\left(R^*\left(\lambda(\sigma)\right) - R\right)d\mathbf{F}(R)\right] \\
&= \left(\phi_1 - \phi_2\sigma\right)\sigma - r + \frac{1}{2\sigma}\left(R^* - \underline{R}\right)^2 + \frac{r}{\lambda\sigma}\left(R^* - \underline{R}\right) \\
&= \frac{\left(\bar{R} - R^*\right)}{\sigma}\left(\frac{\bar{R} - R^*}{2} - \frac{r}{\lambda}\right) > 0 \qquad \text{(S.1.3)}
\end{aligned}$$

Substitute (14)(15) into the first-order condition (13), we have the optimizing condition (16), which can be further written as

$$g\left(\sigma\right) \equiv \frac{\upsilon\left(\sigma\right)}{2\left[\left(\phi_1 - \phi_2\sigma + \frac{1}{2}\right)\sigma - r\left(1 - \psi\sigma^\rho\right)\right]} = 0, \tag{S.1.4}$$

where

$$\upsilon(\sigma) = -(3-\rho)\phi_2\sigma^2 + (1-\rho)\left(\phi_1 + \frac{1}{2}\right)\sigma + (1+\rho)r - (1-\rho)r\psi\sigma^\rho.$$

Therefore, $g(\sigma) = 0$ is equivalent to $\upsilon(\sigma) = 0$.

Under the CAR constraint, we have $\frac{e}{k} = \psi\sigma^\rho < 1$. Then, we have

$$\upsilon(\sigma) > -(3-\rho)\phi_2\sigma^2 + (1-\rho)\left(\phi_1 + \frac{1}{2}\right)\sigma + 2\rho r > \left[-(3-\rho)\phi_2\sigma + (1-\rho)\left(\phi_1 + \frac{1}{2}\right)\right]\sigma.$$

The last equation implies that $\upsilon(\sigma) > 0$ for any $\sigma \in (0, \hat{\sigma})$, where $\hat{\sigma} \equiv \frac{(1-\rho)\left(\phi_1 + \frac{1}{2}\right)}{(3-\rho)\phi_2}$. Moreover, for any $\sigma \in [\hat{\sigma}, \bar{\sigma})$ we have

$$\frac{\partial\upsilon(\sigma)}{\partial\sigma} \equiv \upsilon_\sigma = -2(3-\rho)\phi_2\sigma + (1-\rho)\left(\phi_1 + \frac{1}{2}\right) - (1-\rho)\rho r\psi\sigma^{\rho-1}. \tag{S.1.5}$$

Notice that the RHS in the last equation is less than $-(1-\rho)\left(\phi_1 + \frac{1}{2}\right) - (1-\rho)\rho r\psi\sigma^{\rho-1}$, due to the fact that $-2(3-\rho)\phi_2\sigma + (1-\rho)\left(\phi_1 + \frac{1}{2}\right) \leq -2(3-\rho)\phi_2\hat{\sigma} + (1-\rho)\left(\phi_1 + \frac{1}{2}\right) = -(1-\rho)\left(\phi_1 + \frac{1}{2}\right)$. Therefore, we have

$$\upsilon_\sigma \leq -(1-\rho)\left(\phi_1 + \frac{1}{2}\right) - (1-\rho)\rho r\psi\sigma^{\rho-1} < 0. \tag{S.1.6}$$

We also have

$$\upsilon(\hat{\sigma}) = (1+\rho)r - (1-\rho)r\psi\hat{\sigma}^\rho > 2\rho r > 0, \tag{S.1.7}$$

and

$$\begin{aligned} \upsilon(\bar{\sigma}) &= -(3-\rho)\phi_2\bar{\sigma}^2 + (1-\rho)\left(\phi_1 + \frac{1}{2}\right)\bar{\sigma} + (1+\rho)r - (1-\rho)r\psi\bar{\sigma}^\rho \\ &= -\rho\left[\bar{R}(\sigma) - r\right] - (1-\rho)r\psi\bar{\sigma}^\rho < 0. \end{aligned} \tag{S.1.8}$$

The second line for $\upsilon(\bar{\sigma})$ is obtained by using the definition of $\bar{\sigma}$, the optimal choice of an unconstrained bank, i.e. $3\phi_2\bar{\sigma}^2 = \left(\phi_1 + \frac{1}{2}\right)\bar{\sigma} + r$. The intermediate value theorem implies that there exists a unique $\sigma \in (0, \bar{\sigma})$ that maximizes the bank's expected profit (i.e., Eq. (S.1.4) holds).

We first show that $\frac{\partial\sigma}{\partial\psi} < 0$.. From $\upsilon(\sigma) = 0$, we have $\frac{\mathrm{d}\sigma}{\mathrm{d}\psi} = -\frac{\upsilon_\psi}{\upsilon_\sigma}$. Since $\upsilon_\psi = -(1-\rho)r\sigma^\rho < 0$ and $\upsilon_\sigma < 0$ for any $\sigma \in [\hat{\sigma}, \bar{\sigma})$, we obtain $\frac{\mathrm{d}\sigma}{\mathrm{d}\psi} < 0$.

We next show that $\frac{\partial\sigma}{\partial\rho} < 0$. Based on $\upsilon(\sigma) = -(3-\rho)\phi_2\sigma^2 + (1-\rho)\left(\phi_1 + \frac{1}{2}\right)\sigma + (1+\rho)r - (1-\rho)r\psi\sigma^\rho = 0$, we have

$$\begin{aligned}
\upsilon_\rho &= \phi_2\sigma^2 - (\phi_1 + \frac{1}{2})\sigma + r + r\psi\sigma^\rho - (1-\rho)r\psi\sigma^\rho \log\sigma \\
&= \frac{1}{\rho}\left[3\phi_2\sigma^2 - (\phi_1 + \frac{1}{2})\sigma - r + r\psi\sigma^\rho\right] - (1-\rho)r\psi\sigma^\rho \log\sigma \\
&< -\frac{1}{\rho}\left[-3\phi_2\sigma^2 + (\phi_1 + \frac{1}{2})\sigma + R^*(\sigma)\right] < 0
\end{aligned}$$

The term in the bracket is the F.O.C. for portfolio decision without CAR constraint, which is positive for the problem with CAR constraint. Therefore,

$$\frac{\partial\sigma}{\partial\rho} = -\frac{\upsilon_\rho}{\upsilon_\sigma} < 0$$

□

Proof of Proposition 1.

Proof. Applying the implicit function theorem to $\upsilon(\sigma) = 0$ yields

$$\frac{\mathrm{d}\sigma}{\mathrm{d}r} = -\frac{\upsilon_r}{\upsilon_\sigma} = -\frac{(1+\rho) - (1-\rho)\psi\sigma^\rho}{\upsilon_\sigma}, \tag{S.1.9}$$

where υ_σ is given by (S.1.6). The second equality is from the definition of υ_r. Notice that under the binding CAR constraint, we have $\lambda = \frac{1}{\psi\sigma^\rho} > 1$ and $\upsilon_\sigma < 0$, therefore $(1+\rho) - (1-\rho)\frac{\sigma^\rho}{\psi} > 0$ implying $\frac{\mathrm{d}\sigma}{\mathrm{d}r} > 0$. Moreover, from the CAR constraint we have

$$\frac{\mathrm{d}\lambda}{\mathrm{d}r} = -\frac{\rho}{\psi\sigma^{\rho-1}}\frac{\mathrm{d}\sigma}{\mathrm{d}r} < 0. \tag{S.1.10}$$

As $r = \frac{r_d - \theta}{1-\theta}$, so $\frac{\mathrm{d}\sigma}{\mathrm{d}\theta} = \frac{r_d - 1}{(1-\theta)^2}\frac{\mathrm{d}\sigma}{\mathrm{d}r}$. Therefore,

$$\frac{\mathrm{d}\sigma}{\mathrm{d}\theta} > 0, \ \frac{\mathrm{d}\lambda}{\mathrm{d}\theta} < 0.$$

□

Proof of Proposition 2.

Proof. Taking second-order derivations, we have

$$\frac{\partial^2\sigma}{\partial r\partial\rho} = \frac{\partial}{\partial\rho}\left[-\frac{\upsilon_r}{\upsilon_\sigma}\right] = \frac{-\upsilon_{r\rho}\upsilon_\sigma + \upsilon_{r\sigma}\upsilon_\rho + \upsilon_{\sigma\rho}\upsilon_r - \upsilon_r\upsilon_\rho\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}}{\upsilon_\sigma^2}$$

From $\upsilon(\sigma) = 0$, we have

$$(3-\rho)\phi_2\sigma^2 = (1+\rho)r + (1-\rho)\left[\left(\phi_1 + \frac{1}{2}\right)\sigma - r\psi\sigma^\rho\right] > (1+\rho)r$$

Substitute into $\upsilon_{\sigma\sigma}$, we have

$$\begin{aligned}\upsilon_{\sigma\sigma} &= -2\left(3-\rho\right)\phi_2 + \rho\left(1-\rho\right)^2 r\psi\sigma^{\rho-2} \\ &< -\frac{r}{\sigma^2}\left[2\left(1+\rho\right) - \rho\left(1-\rho\right)^2\psi\sigma^{\rho}\right] < 0\end{aligned}$$

As $\upsilon_\sigma < 0, \upsilon_r > 0, \upsilon_\rho < 0$, we obtain that $\upsilon_r\upsilon_\rho\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma} < 0$. So

$$\frac{\partial^2\sigma}{\partial r\partial\rho} > \frac{-\upsilon_{r\rho}\upsilon_\sigma + \upsilon_{r\sigma}\upsilon_\rho + \upsilon_{\sigma\rho}\upsilon_r}{\upsilon_\sigma^2}$$

It is easy to show that

$$\begin{aligned}&\upsilon_{r\sigma}\upsilon_\rho + \upsilon_r\upsilon_{\sigma\rho} - \upsilon_\sigma\upsilon_{r\rho} \\ =&8\phi_2\sigma - 2\left(\phi_1+\frac{1}{2}\right) + \left(1-\rho\right)\left(1+\rho\right)\psi\sigma^\rho\left[\left(\phi_1+\frac{1}{2}\right) - \frac{2+\rho}{1+\rho}\phi_2\sigma - \frac{r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\right] \\ &+\psi\sigma^\rho\Big[1-\left(1-\rho\right)\log\sigma\Big]\left[2\left(3-\rho\right)\phi_2\sigma - \left(1-\rho\right)\left(\phi_1+\frac{1}{2}\right) + \rho\left(1+\rho\right)\frac{r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\right] \\ =&\underbrace{8\phi_2\sigma - 2\left(\phi_1+\frac{1}{2}\right) + \left(1-\rho\right)\psi\sigma^\rho\left[2\left(\phi_1+\frac{1}{2}\right) - 5\phi_2\sigma\right]}_{\equiv\Omega} \\ &+\psi\sigma^\rho\Big[1-\left(1-\rho\right)\log\sigma\Big]\left[\left(3-\rho\right)\phi_2\sigma + \left(1+\rho\right)^2\frac{r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\right]\end{aligned}$$

where we substitute with $\upsilon\left(\sigma\right)=0$ in the second equality.

We then show that $\Omega > 0$. First, with $\sigma > \frac{(1-\rho)\left(\phi_1+\frac{1}{2}\right)}{(3-\rho)\phi_2}$, we have

$$\Omega > \frac{\phi_1+\frac{1}{2}}{3-\rho}\left[2\left(1-3\rho\right) + \left(1+3\rho\right)\left(1-\rho\right)\psi\sigma^\rho\right] > 0$$

The last inequality holds for relatively small ρ, i.e. $\rho \leq \frac{1}{3}$. Second, with $\upsilon\left(\sigma\right)=0$,

$$2\phi_2\sigma^2 = \left(1+\rho\right)r + \left(1-\rho\right)\left[\underbrace{\left(\phi_1+\frac{1}{2}-\phi_2\sigma\right)\sigma}_{=\bar{R}} - r\psi\sigma^\rho\right] > \left(1+\rho\right)r$$

Substitute into Ω, we have

$$\begin{aligned}\Omega &> \left\{\frac{3}{4}\frac{\left(1+\rho\right)\left[2-\left(1-\rho\right)\psi\sigma^\rho\right]}{\left[1-\left(1-\rho\right)\psi\sigma^\rho\right]} - \frac{\bar{R}}{r}\right\}2\left[1-\left(1-\rho\right)\psi\sigma^\rho\right]\frac{r}{\sigma} \\ &> \left[\frac{3}{2}\left(1+\rho\right) - \frac{\bar{R}}{r}\right]2\left[1-\left(1-\rho\right)\psi\sigma^\rho\right]\frac{r}{\sigma} > 0\end{aligned}$$

For $\rho > \frac{1}{3}$, the last inequality holds for $\bar{R} < 2r$.

In conclusion, we obtain

$$\frac{\partial^2\sigma}{\partial r\partial\rho} = \frac{\upsilon_{r\sigma}\upsilon_\rho + \upsilon_{\sigma\rho}\upsilon_r - \upsilon_{r\rho}\upsilon_\sigma}{\upsilon_\sigma^2} - \frac{\upsilon_r\upsilon_\rho\upsilon_{\sigma\sigma}}{\upsilon_\sigma^3} > \frac{\Omega}{\upsilon_\sigma^2} > 0$$

Therefore, $\frac{\partial^2\sigma}{\partial\theta\partial\rho} = \frac{\partial^2\sigma}{\partial r\partial\rho}\frac{r_d-1}{(1-\theta)^2} > 0$. □

Lemma 2. The sensitivity of bank risk-taking to changes in monetary policy (i.e., $\frac{\partial\sigma}{\partial\theta}$) decreases with the required capitalization level ψ, or equivalently, $\frac{\partial^2\sigma}{\partial\theta\partial\psi} < 0$.

Proof. Taking second-order derivations, we have

$$\begin{aligned}\frac{\partial^2\sigma}{\partial r\partial\psi} &= \frac{\partial}{\partial\psi}\left[-\frac{\upsilon_r}{\upsilon_\sigma}\right] = \frac{-\upsilon_{r\psi}\upsilon_\sigma + \upsilon_{\sigma r}\upsilon_\psi + \upsilon_r\upsilon_{\sigma\psi} - \upsilon_r\upsilon_\psi\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}}{\upsilon_\sigma^2} \\ &= -\frac{(1-\rho)\,\sigma^\rho}{\upsilon_\sigma^2}\left[2\,(3-\rho)\,\phi_2\sigma - (1-\rho)\left(\phi_1+\frac{1}{2}\right) + \frac{(1+\rho)\,r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\left(\rho-\frac{\sigma\upsilon_{\sigma\sigma}}{\upsilon_\sigma}\right)\right] \\ &= -\frac{(1-\rho)\,\sigma^\rho}{\upsilon_\sigma^2}\left[(3-\rho)\,\phi_2\sigma + \frac{(1+\rho)\,r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\left(1+\rho-\sigma\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}\right)\right]\end{aligned}$$

The last line is obtained with $\upsilon(\sigma) = 0$. Therefore, $\frac{\partial^2\sigma}{\partial r\partial\psi}$ can be further expressed as

$$\frac{\partial^2\sigma}{\partial r\partial\psi} = -\frac{1-\rho}{\upsilon_\sigma^3}\sigma^\rho\Psi, \tag{S.1.11}$$

where

$$\begin{aligned}\Psi &= (3-\rho)\,\phi_2\sigma\upsilon_\sigma + \frac{(1+\rho)\,r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\left[(1+\rho)\,\upsilon_\sigma - \sigma\upsilon_{\sigma\sigma}\right], \\ \upsilon_{\sigma\sigma} &= -2\,(3-\rho)\,\phi_2 + (1-\rho)^2\,\rho r\psi\sigma^{\rho-2}, \\ \upsilon_\sigma &= -2\,(3-\rho)\,\phi_2\sigma + (1-\rho)\left(\phi_1+\frac{1}{2}\right) - (1-\rho)\,\rho r\psi\sigma^{\rho-1}.\end{aligned}$$

Since we have $\upsilon_\sigma < 0$, to $\frac{\partial^2\sigma}{\partial r\partial\psi} < 0$ is equivalent to $\Psi < 0$. We simplify Ψ as

$$\Psi = -(3-\rho)\,\phi_2\sigma\left[(3-\rho)\,\phi_2\sigma + \frac{\rho\,(1+\rho)\,r}{\sigma}\right] - (1+\rho)\,\frac{r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\Xi, \tag{S.1.12}$$

where $\Xi = \left[(3-\rho)\,\phi_2\,(\rho+1)\,\sigma - (1-\rho)\,(1+\rho)\left(\phi_1+\frac{1}{2}\right) + 2\,(1-\rho)\,\rho r\psi\sigma^{\rho-1}\right]$. Notice that from the previous analysis, we have $\sigma > \hat{\sigma} = \frac{(1-\rho)\left(\phi_1+\frac{1}{2}\right)}{(3-\rho)\phi_2}$. Therefore, we obtain

$$\Xi > (3-\rho)\,\phi_2\,(\rho+1)\,\sigma - (1-\rho)\,(1+\rho)\left(\phi_1+\frac{1}{2}\right) > 0, \tag{S.1.13}$$

which implies that $\Psi < 0$, and thereby $\frac{\partial^2\sigma}{\partial r\partial\psi} < 0$. Therefore, $\frac{\partial^2\sigma}{\partial\theta\partial\psi} = \frac{r_d-1}{(1-\theta)^2}\frac{\partial^2\sigma}{\partial r\partial\psi} < 0$ □

Proof of Proposition 3.

Proof. For an individual bank with idiosyncratic risk Δ, the proof of the existence and uniqueness of the solution to the optimizing problem is similar to the proof for Proposition 1. The bank's optimal project choice σ^* solves that $\upsilon(\sigma;\Delta) = 0$, where $\upsilon(\sigma;\Delta)$ is given by

$$\upsilon(\sigma;r,\Delta) = -(3-\rho)\,\phi_2\sigma^2 + (1-\rho)\left(\phi_1+\frac{1}{2}\Delta\right)\sigma + (1+\rho)\,r - (1-\rho)\,r\psi\,(\Delta\sigma)^\rho\,.$$

Applying the implicit function theorem to the optimal condition $\nu(\sigma;\Delta)=0$ yields

$$\begin{aligned}\frac{\partial\sigma}{\partial\Delta} &= -\frac{\nu_\Delta}{\nu_\sigma} = -\frac{(1-\rho)\,\sigma}{2\nu_\sigma}\left[1-\frac{2\rho r\psi}{(\Delta\sigma)^{1-\rho}}\right] \\ &> -\frac{(1-\rho)\,\sigma}{2\nu_\sigma}\left(1-2\rho r\psi\right) > 0\end{aligned}$$

where the last inequality obtains under the assumptions that $\rho r\psi < \frac{1}{2}$ because $\nu_\sigma <$ 0. □

Proof of Proposition 4.

Proof. We first prove $\frac{\partial^2\sigma}{\partial\Delta\partial\rho} < 0$, which is equivalent to

$$\frac{\partial}{\partial\Delta}\left[-\frac{\upsilon_\rho}{\upsilon_\sigma}\right] = \frac{\upsilon_{\rho\sigma}\upsilon_\Delta + \upsilon_\rho\upsilon_{\sigma\Delta} - \upsilon_{\rho\Delta}\upsilon_\sigma - \upsilon_\rho\upsilon_\Delta\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}}{\upsilon_\sigma^2} < 0.$$

It is easy to show that

$$\begin{aligned}\upsilon_{\rho\sigma}\upsilon_\Delta + \upsilon_\rho\upsilon_{\sigma\Delta} - \upsilon_{\rho\Delta}\upsilon_\sigma &= \frac{(1-\rho)}{2}\left[3\phi_2\sigma^2 - \left(\phi_1+\frac{1}{2}\Delta\right)\sigma + r\right] - (3-\rho)\,\phi_2\sigma^2 \\ &\quad - r\psi\Delta^{\rho-1}\sigma^{\rho-1}\left[\begin{array}{c}\left(3-8\rho-\rho^2\right)\phi_2\sigma^2 + 2\rho r - \rho\frac{(1-\rho)}{2}\Delta\sigma \\ +(1-\rho)^2\,r\left(1-\psi\Delta^\rho\sigma^\rho\right)\end{array}\right],\end{aligned}$$

and

$$-\upsilon_\rho\upsilon_\Delta\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma} = -\frac{(1-\rho)}{2}\sigma\nu_\rho\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma} + (1-\rho)\,\rho r\psi\Delta^{\rho-1}\sigma^\rho\upsilon_\rho\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}.$$

Therefore, we obtain

$$\begin{aligned}&\upsilon_{\rho\sigma}\upsilon_\Delta + \upsilon_\rho\upsilon_{\sigma\Delta} - \upsilon_{\rho\Delta}\upsilon_\sigma - \upsilon_\rho\upsilon_\Delta\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma} \\ &< -\frac{(1-\rho)}{2}\sigma\nu_\rho\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma} + \frac{(1-\rho)}{2}\left[3\phi_2\sigma^2 - \left(\phi_1+\frac{1}{2}\Delta\right)\sigma + r\right] - (3-\rho)\,\phi_2\sigma^2 \\ &= \frac{(1-\rho)}{\upsilon_\sigma}\left\{\frac{(3-\rho)}{(1-\rho)}\phi_2^2\sigma^3 + r\left[3\phi_2\sigma + \frac{(1-\rho)}{2}\left(\phi_1+\frac{1}{2}\Delta\right)\right]\left(1-\psi\Delta^\rho\sigma^\rho\right)\right. \\ &+ \frac{6\rho r\phi_2\sigma}{(1-\rho)} + \frac{(1+\rho)\,r}{2}\left(\phi_1+\frac{1}{2}\Delta\right) - r\psi\Delta^\rho\sigma^{\rho-1}\frac{(2-\rho)(1-\rho)}{2}\rho r \\ &+ r\psi\Delta^\rho\sigma^{\rho-1}\left[\left((3-\rho)\,\phi_2\sigma^2 - \frac{(1-\rho)^2}{2}\rho r\psi\Delta^\rho\sigma^\rho\right)\left(1-(1-\rho)\log(\Delta\sigma)\right)\right. \\ &\left.\left. + \frac{(1-\rho)(2-\rho)\,\rho}{2}\left(\phi_1+\frac{1}{2}\Delta\right)\sigma + \rho\frac{2+3\rho-\rho^2}{2}\phi_2\sigma^2\right]\right\} \\ &< 0.\end{aligned}$$

The last inequality holds as $v_\sigma < 0$, $\sigma > \hat{\sigma}$, and $\bar{R}(\sigma, \Delta) > r$, i.e.

$$\frac{6\rho r\phi_2\sigma}{(1-\rho)} - r\psi\Delta^\rho\sigma^{\rho-1}\frac{(2-\rho)(1-\rho)}{2}\rho r > 6\rho r\frac{\phi_1 + \frac{1}{2}\Delta}{3-\rho} - \frac{r}{\lambda\sigma}\frac{(2-\rho)(1-\rho)}{2}\rho r$$
$$> \frac{\rho r}{\sigma}\left[\frac{6}{3-\rho}\bar{R}(\sigma,\Delta) - r\frac{(2-\rho)(1-\rho)}{2}\right] > \frac{\rho r^2}{\sigma}\left[2 - \frac{(2-\rho)(1-\rho)}{2}\right] > 0$$

and

$$(3-\rho)\phi_2\sigma^2 - \frac{(1-\rho)^2}{2}\rho r\psi\Delta^\rho\sigma^\rho > (1-\rho)\left[\left(\phi_1 + \frac{1}{2}\Delta\right)\sigma - \frac{\rho(1-\rho)}{2}\frac{r}{\lambda}\right]$$
$$> (1-\rho)\left[\bar{R}(\sigma,\Delta) - \frac{\rho(1-\rho)}{2}r\right] > (1-\rho)r\left[1 - \frac{\rho(1-\rho)}{2}\right] > 0.$$

We then prove $\frac{\partial}{\partial\Delta}\left[\frac{\partial\sigma}{\partial\theta}|_{\rho=1} - \frac{\partial\sigma}{\partial\theta}|_{\rho=0}\right] > 0$. In the limit with $\rho = 0$, the sensitivity of bank risk-taking to the monetary policy shock satisfies

$$\frac{\partial\sigma}{\partial r}|_{\rho=0} = \frac{1-\psi}{\sqrt{\left(\phi_1 + \frac{1}{2}\Delta\right)^2 + 12r(1-\psi)\phi_2}} > 0., \tag{S.1.14}$$

which decreases with the bank's idiosyncratic risk Δ. In the other limit with $\rho = 1$, the sensitivity becomes

$$\frac{\partial\sigma}{\partial r}|_{\rho=1} = \sqrt{\frac{(1+\rho)}{(3-\rho)\phi_2}}\frac{1}{2\sqrt{r}} = \frac{1}{2\sqrt{r\phi_2}}, \tag{S.1.15}$$

which is independent of Δ.

From the last two equations, we can derive the impact of regulatory change on the sensitivity of bank risk-taking to monetary policy shocks

$$\frac{\partial\sigma}{\partial r}|_{\rho=1} - \frac{\partial\sigma}{\partial r}|_{\rho=0} = \frac{1}{2\sqrt{r\phi_2}} - \frac{1-\psi}{\sqrt{\left(\phi_1 + \frac{1}{2}\Delta\right)^2 + 12r(1-\psi)\phi_2}} > 0,$$

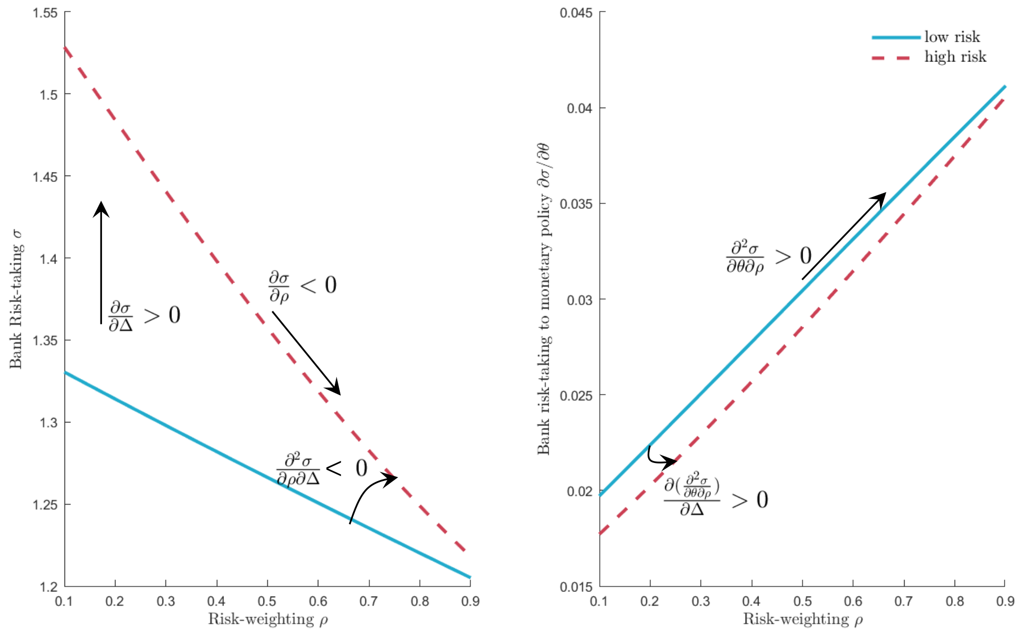
which is increasing in the bank-specific risk Δ. Therefore, $\frac{\partial}{\partial\Delta}\left[\frac{\partial\sigma}{\partial r}|_{\rho=1} - \frac{\partial\sigma}{\partial r}|_{\rho=0}\right] > 0$, and

$$\frac{\partial}{\partial\Delta}\left[\frac{\partial\sigma}{\partial\theta}|_{\rho=1} - \frac{\partial\sigma}{\partial\theta}|_{\rho=0}\right] = \frac{r_d - 1}{(1-\theta)^2}\frac{\partial}{\partial\Delta}\left[\frac{\partial\sigma}{\partial r}|_{\rho=1} - \frac{\partial\sigma}{\partial r}|_{\rho=0}\right] > 0.$$

□

Figure S.1.1 illustrates the effects of regulatory policy changes on bank risk-taking. The graphs are drawn based on numerical simulations of the model. The left panel shows the average relation between a bank's choice of the project risk σ and the risk-weighting sensitivity ρ at different levels of the idiosyncratic risk Δ. Given a low level of Δ, the bank takes less risk when the risk-weighting sensitivity increases, implying a downward-sloping relation between σ and ρ (the solid line), as stated in Lemma 1. For a given value of ρ, an increase in Δ leads to more risk taking, shifting the curve upward (the dashed line), as formally stated in Proposition 3. A bank with a higher level of Δ

FIGURE S.1.1. Bank risk-taking under regulatory changes and monetary policy



Notes: This figure illustrates how bank risk-taking behaviors depend on capital regulations and monetary policy for a bank with a high idiosyncratic risk (dashed line) and a low idiosyncratic risk (solid line). The x-axis is the risk-weighting sensitivity ρ. The y-axis in the left panel is the bank's choice of risk-taking σ, and the y-axis in the right panel is the response of bank risk-taking to monetary policy changes $\frac{\partial\sigma}{\partial\theta}$. All the lines are based on a numerical simulation in the model, with the parameter values set to $\phi_1 = 2, \phi_2 = 0.75, r \equiv \frac{r_d-\theta}{1-\theta} = 1.05, \tilde{\psi} = 0.2, \Delta_{low} = 0.8, \Delta_{high} = 2$.

also reduces risk-taking more aggressively in response to an increase in ρ (i.e., the line becomes steeper at a larger Δ), consistent with Proposition 4.

The right panel of Figure S.1.1 shows the relation between the sensitivity of bank risk-taking to monetary policy easing and the capital regulation parameter ρ at different values of idiosyncratic risk Δ. At given values of ρ and Δ, the value of $\frac{\partial\sigma}{\partial\theta}$ is positive, indicating that a monetary policy expansion (i.e., a decline in RR) reduces risk taking, confirming the result in Proposition 1. The curves are upward sloping, indicating that monetary policy easing would lead to a larger reduction in risk taking at a higher value of ρ, in line with Proposition 2. Furthermore, an increase in Δ would lead to a counter-clockwise rotation of the curve (from the solid line to the dashed line), leading to a steeper slope of the relation between $\frac{\partial\sigma}{\partial\theta}$ and ρ. Thus, following a monetary policy expansion, a bank with a higher idiosyncratic risk would reduce risk-taking more aggressively when the risk-weighting sensitivity becomes higher. This confirms the result stated in Proposition 4.

Appendix S.2. A model with bank market power

We consider the bank's market power in the loan market to provide an alternative mechanism for identifying the effects of regulatory changes on the bank's risk-taking.[10] We assume that the payoff for project σ includes two components, $g(K)\,R(\sigma)$. The first part, $g(K) = AK^{\alpha-1}$, is marginal return on aggregate capital. Aggregate capital K is financed by loans from individual banks indexed by i, with the constant-elasticity-of-substitution (CES) aggregation technology

$$K = \left(\frac{1}{N}\sum_{i=1}^{N} k_i^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, \tag{S.2.1}$$

where the number of banks, N, captures the competition level of the loan market, and k_i is the loan supply of an individual bank i. The second part of the project payoff, $R(\sigma)$, is project-specific, which is the same as our baseline model.

An individual bank takes as given the other bank's decision, and chooses σ and λ to solve the profit-maximizing problem,

$$V = e \max_{\{\sigma,d\}} \int_{\underline{R}(\sigma)}^{\bar{R}(\sigma)} \max\left\{g(K)\,R\lambda - r(\lambda-1), 0\right\} \mathrm{d}\mathbf{F}(R), \tag{S.2.2}$$

subject to the flow-of-funds constraint (5) and the CAR constraint (6) in the main text.

With a binding CAR constraint, we can rewrite the bank's objective function as

$$V = \max_{\{\sigma\}} \frac{eg(K)}{2\psi\sigma^{\rho+1}} \left[\bar{R}(\sigma) - R^*(\sigma;K)\right]^2, \tag{S.2.3}$$

where the break-even level of project return is given by

$$R^*(\sigma;K) = \frac{r(1-\psi\sigma^{\rho})}{g(K)}. \tag{S.2.4}$$

The first-order condition for the optimizing choice of σ implies that

$$\frac{(\rho+1)}{2\sigma}\left[\bar{R}(\sigma) - R^*(\sigma;K)\right] = \frac{\partial\left[\bar{R}(\sigma) - R^*(\sigma;K)\right]}{\partial\sigma} + \frac{\partial g(K)/\partial\sigma}{2g(K)}\left[\bar{R}(\sigma) + R^*(\sigma;K)\right]. \tag{S.2.5}$$

The bank's market power in the loan market creates an additional benefit of the bank's risk-taking, indicated by the second term in the right-hand side of the above equation. A riskier project σ would tighten the CAR constraint, reducing the bank's lending supply. Due to the bank's market power, a reduction in an individual bank's lending supply

[10] We focus on banking competition in loan markets because loan markets in China are segmented while deposit markets are nationwide. Our results hold the same for deposit markets. The revenue is more sensitive to an individual's loan supply in a more concentrated credit market. At the same time, the cost is also more sensitive to an individual bank's deposit demand in a more concentrated deposit market.

would reduce the total capital outstanding and raise the marginal return $g(K)$, which increases the bank's profits. This additional benefit would encourage the bank's risk-taking, leading to a riskier project σ compared to the baseline model.

In a symmetric equilibrium, all the individual banks make the same decision, and thus, $K = k_i$ for all i. The effects of risk-taking (σ_i) on capital return is determined by

$$\frac{\partial g(K)}{\partial \sigma_i} / g(K) = \frac{(1-\alpha)\rho}{N\sigma}, \tag{S.2.6}$$

which decreases with the competition level of the loan market (N). In a more competitive market, the marginal benefit of risk-taking is lower, discouraging bank risk-taking (σ). This result is formally stated in Proposition S.2.1.

Proposition S.2.1. *The optimal project risk (σ) decreases with the level of banking competition (N), that is,*

$$\frac{\partial \sigma}{\partial N} < 0. \tag{S.2.7}$$

Proof. We first show the existence of the bank's optimal project choice σ^*. The first-order condition (S.2.5) can be written as

$$\begin{aligned} \upsilon(\sigma) = & \left(1 - \rho + \frac{(1-\alpha)\rho}{N}\right)\left(\phi_1 + \frac{1}{2}\right)\sigma - \left(3 - \rho + \frac{(1-\alpha)\rho}{N}\right)\phi_2\sigma^2 \\ & + \frac{r}{g(K)}\left[\left(1 + \frac{(1-\alpha)\rho}{N}\right)(1 - \psi\sigma^\rho) + \rho(1 + \psi\sigma^\rho)\right] = 0. \end{aligned}$$

Second-order derivation is given by,

$$\begin{aligned} \upsilon_\sigma = & \left(1 - \rho + \frac{(1-\alpha)\rho}{N}\right)\left(\phi_1 + \frac{1}{2}\right) - 2\left(3 - \rho + \frac{(1-\alpha)\rho}{N}\right)\phi_2\sigma - \frac{\rho r\psi\sigma^{\rho-1}}{g(K)}\left[1 - \rho + \frac{(1-\alpha)\rho}{N}\right] \\ & - \frac{(1-\alpha)\rho r}{N\sigma g(K)}\left[\left(1 + \frac{(1-\alpha)\rho}{N}\right)(1 - \psi\sigma^\rho) + \rho(1 + \psi\sigma^\rho)\right]. \end{aligned}$$

Obviously, for $\sigma \geq \hat{\sigma} = \frac{\left(1-\rho+\frac{(1-\alpha)\rho}{N}\right)\left(\phi_1+\frac{1}{2}\right)}{\left(3-\rho+\frac{(1-\alpha)\rho}{N}\right)\phi_2}$, $\upsilon_\sigma < 0$, and $\upsilon(\sigma)$ is decreasing in σ. For $\sigma = \hat{\sigma}$,

$$\upsilon(\hat{\sigma}) = \frac{r}{g(K)}\left[\left(1 + \frac{(1-\alpha)\rho}{N}\right)(1 - \psi\sigma^\rho) + \rho(1 + \psi\sigma^\rho)\right] > 0.$$

Define $\bar{\sigma}$ as the optimal choice of an individual bank without CAR constraint, or the unconstrained bank. So $\bar{\sigma}$ satisfies that

$$\left(\phi_1 + \frac{1}{2}\right)\sigma - 3\phi_2\sigma^2 + \frac{r\left(1 - 1/\bar{\lambda}\right)}{g(K)} = 0,$$

where $\bar{\lambda}$ is determined by

$$\left[1 - \frac{(1-\alpha)}{N}\right]\left[\left(\phi_1 - \phi_2\bar{\sigma} + \frac{1}{2}\right)\bar{\sigma} + \frac{r\left(1 - 1/\bar{\lambda}\right)}{g(K)}\right] - \frac{2r}{g(K)} = 0.$$

For $\sigma = \bar{\sigma}$,

$$\begin{aligned} \upsilon(\bar{\sigma}) =& -\rho\left(1-\frac{1-\alpha}{N}\right)\bar{R}+\frac{\rho r\left(1+\psi\bar{\sigma}^{\rho}\right)+r\left(1/\bar{\lambda}-\psi\bar{\sigma}^{\rho}\right)}{g(K)}+\frac{(1-\alpha)\rho}{N}\frac{r\left(1-\psi\bar{\sigma}^{\rho}\right)}{g(K)} \\ =& \frac{r\left(1/\bar{\lambda}-1/\lambda(\bar{\sigma})\right)}{g(K)}\left[1-\rho\left(1-\frac{1-\alpha}{N}\right)\right]<0 \end{aligned}$$

where $\lambda(\bar{\sigma}) = 1/\left(\psi\bar{\sigma}^{\rho}\right)$ is the bank's leverage with binding CAR constraint, which is less than that of the unconstrained bank, $\bar{\lambda}$. Therefore, there exists a unique $\sigma^* \in (\hat{\sigma}, \bar{\sigma})$ that solves $\upsilon(\sigma^*) = 0$.

From $\upsilon(\sigma) = 0$, we have $\frac{\partial\sigma}{\partial N} = -\frac{\upsilon_N}{\upsilon_\sigma} = -\frac{\upsilon_N}{\upsilon_\sigma}$. As $\upsilon_N = -\frac{(1-\alpha)\rho}{N^2}\left[\left(\phi_1-\phi_2\sigma+\frac{1}{2}\right)\sigma+\frac{r(1-\psi\sigma^{\rho})}{g(K)}\right] < 0$ for any $\rho \in (0,1)$, and $\upsilon_\sigma < 0$ for any $\sigma \in (\hat{\sigma}, \bar{\sigma})$, we can obtain $\frac{\partial\sigma}{\partial N} < 0$. □

In general, the impact of regulatory changes (in particular, changes in the risk-weighting sensitivity ρ) on bank risk-taking depends on the level of banking competition (N). In a regime with a higher level of ρ, the bank's market power (S.2.6) is more sensitive to the banking competition level (N), leading to a greater reduction in bank risk-taking.

Following an expansionary monetary policy, the bank reduces risk-taking (σ) to boost leverage. When regulatory policy raises the risk-weighting sensitivity (ρ), the bank risk-taking (σ) would become more sensitive to market competition (N) Thus, under a regulatory policy with a higher ρ, banks facing more loan market competition would reduce risk-taking more aggressively following a monetary policy expansion.

To summarize, the effects of raising the risk-weighting sensitivity ρ on risk-taking are amplified by the level of banking competition N. These results are formally stated in Proposition S.2.2.

Proposition S.2.2. *Under a higher level of the risk-weighting sensitivity (e.g., when ρ increases from 0 to 1), a bank facing a greater level of banking competition (N) reduces risk-taking (σ) more aggressively, that is,*

$$\frac{\partial\sigma}{\partial N}|_{\rho=1} - \frac{\partial\sigma}{\partial N}|_{\rho=0} < 0$$

Furthermore, the reduction is more aggressive following an expansionary monetary policy shock. In particular, we have,

$$\frac{\partial}{\partial N}\left[\frac{\partial\sigma}{\partial\theta}|_{\rho=1} - \frac{\partial\sigma}{\partial\theta}|_{\rho=0}\right] > 0. \tag{S.2.8}$$

Proof. For $\rho = 0$, $\upsilon_N = 0$, and thus $\frac{\partial\sigma}{\partial N} = 0$. For $\rho = 1$, $\frac{\partial\sigma}{\partial N} < 0$. So we have that $\frac{\partial\sigma}{\partial N}|_{\rho=1} - \frac{\partial\sigma}{\partial N}|_{\rho=0} < 0$.

For second-order derivation,

$$\frac{\partial^2\sigma}{\partial r\partial N} = \frac{\partial\sigma}{\partial N}\left[-\frac{\upsilon_r}{\upsilon_\sigma}\right] = \frac{\upsilon_{r\sigma}\upsilon_N - \upsilon_{rN}\upsilon_\sigma + \upsilon_r\upsilon_{\sigma N} - \frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}\upsilon_r\upsilon_N}{\upsilon_\sigma^2}$$

It is easy to show that,

$$
\begin{aligned}
& \upsilon_{r\sigma}\upsilon_N - \upsilon_{rN}\upsilon_\sigma + \upsilon_r\upsilon_{\sigma N} \\
=& \frac{(1-\alpha)\,\rho}{N^2 g(K)}\left\{ \left(\phi_1 - \phi_2\sigma + \frac{1}{2}\right)\frac{(1-\alpha)\,\rho}{N}\left[\left(1+\frac{(1-\alpha)\,\rho}{N}\right)(1-\psi\sigma^\rho) - 2 + \rho\,(1+\psi\sigma^\rho)\right]\right. \\
& + \frac{r\left[(1-\psi\sigma^\rho)\left(1+\frac{(1-\alpha)\rho}{N}\right)+\rho\,(1+\psi\sigma^\rho)\right]}{g(K)\,\sigma}\left[\frac{2\,(1-\alpha)\,\rho}{N}(1-\psi\sigma^\rho)+\rho\psi\sigma^\rho-(1-\rho)\,(1+\psi\sigma^\rho)\right] \\
& \left. + 2\,(1+\rho+2\psi\sigma^\rho)\,\phi_2\sigma - 2\left(\phi_1+\frac{1}{2}\right) + \left(\phi_1-\phi_2\sigma+\frac{1}{2}\right)\rho\psi\sigma^\rho\left[1-\rho+\frac{(1-\alpha)\,\rho}{N}\right]\right\} \\
>& -\frac{(1-\alpha)\,\rho}{N^2\sigma g(K)}2\left[\phi_1+\frac{1}{2}-(1+\rho)\,\phi_2\sigma\right]
\end{aligned}
$$

The last inequality holds for $\rho = 1$. For $\rho = 1$, we have

$$
-\frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}\upsilon_r\upsilon_N = \frac{(1-\alpha)\,\rho}{N^2 g(k)}\left[2\left(\phi_1-\phi_2\sigma+\frac{1}{2}\right)+\Psi\right]
$$

where

$$
\begin{aligned}
\Psi =& \frac{8\phi_2\frac{r(1-\psi\sigma^\rho)}{g(k)} + 2\bar{R}\frac{(1-\alpha)}{N\sigma^2}\left[\bar{R}+(3-2\psi\sigma^\rho)\,\phi_2\sigma^2-\frac{r(4+\psi\sigma^\rho)}{g(k)}\right]}{4\phi_2\sigma-\frac{(1-\alpha)}{N}\left[\phi_1+\frac{1}{2}-2\phi_2\sigma-\frac{r(2+\psi\sigma^\rho)}{g(k)\sigma}\right]} \\
& + \frac{4\frac{(1-\alpha)}{N\sigma}\frac{r(1-\psi\sigma^\rho)}{g(k)}\left[(2-\psi\sigma^\rho)\,\sigma-\frac{r}{g(k)\sigma}\right]}{4\phi_2\sigma-\frac{(1-\alpha)}{N}\left[\phi_1+\frac{1}{2}-2\phi_2\sigma-\frac{r(2+\psi\sigma^\rho)}{g(k)\sigma}\right]}
\end{aligned}
$$

We ignore the terms of $\frac{1-\alpha}{N}$ with orders greater than 1 in the definition of Ψ. From $\upsilon(\sigma) = 0$, we have $\phi_2\sigma^2 > r$. With the assumption that $\frac{(1-\alpha)}{N}\bar{R} < r$, we obtain that $\Psi > 0$.

Therefore, for $\rho = 1$, we have

$$
\begin{aligned}
\frac{\partial^2\sigma}{\partial r\partial N} &= \frac{\upsilon_{r\sigma}\upsilon_N - \upsilon_{rN}\upsilon_\sigma + \upsilon_r\upsilon_{\sigma N} - \frac{\upsilon_{\sigma\sigma}}{\upsilon_\sigma}\upsilon_r\upsilon_N}{\upsilon_\sigma^2} \\
&> \frac{(1-\alpha)\,\rho}{N^2 g(K)}\left\{-2\left[\phi_1+\frac{1}{2}-(1+\rho)\,\phi_2\sigma\right]+2\left(\phi_1-\phi_2\sigma+\frac{1}{2}\right)\right\} \\
&= \frac{(1-\alpha)\,\rho}{N^2 g(K)}2\rho\phi_2\sigma > 0,
\end{aligned}
$$

Obviously, for $\rho = 0$, $\frac{\partial^2\sigma}{\partial r\partial N} = 0$. Thus we obtain that $\frac{\partial}{\partial N}\left[\frac{\partial\sigma}{\partial r}|_{\rho=1} - \frac{\partial\sigma}{\partial r}|_{\rho=0}\right] > 0$. Therefore,

$$
\frac{\partial}{\partial N}\left[\frac{\partial\sigma}{\partial\theta}|_{\rho=1}-\frac{\partial\sigma}{\partial\theta}|_{\rho=0}\right] = \frac{r_d-1}{(1-\theta)^2}\frac{\partial}{\partial N}\left[\frac{\partial\sigma}{\partial r}|_{\rho=1}-\frac{\partial\sigma}{\partial r}|_{\rho=0}\right] > 0.
$$

□

Appendix S.3. Exogeneity tests of the monetary policy shock

We test the exogeneity of our measure of monetary policy shocks following the same approach as in Chen et al. (2018), with the sample extended to 2017:Q4 (from their 2016:Q2). We find that the measure is orthogonal to other quantity-based policy instruments such as the required reserve ratio (RRR), and price-based policy instruments (targets) such as Repo and SHIBOR, suggesting that it is exogenous to the state of the economy. Table S.3.1 reports the detailed results.

For the robustness analysis, we have considered an alternative measure of monetary policy shocks based on an estimated Taylor rule. A similar test suggests that the exogenous component of the short-term nominal interest rate—that is, the gap between the actual interest rate and the endogenous component capturing systematic reactions of policy to the state of the economy—is unrelated to changes in other policy instruments.

Table S.3.1. Endogenous vs. exogenous components in the M2 growth rule

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Components in MP	Endo MP	MPShock	Endo MP	MPShock	Endo MP	MPShock	Endo MP	MPShock	Endo MP	MPShock	Endo MP	MPShock	Endo MP	MPShock
RRR	-0.0461**	-0.00130												
	(0.0178)	(0.0145)												
DR1			-0.893***	-0.227										
			(0.165)	(0.158)										
DR7					-0.756***	-0.180								
					(0.131)	(0.130)								
DR30							-0.585***	-0.157						
							(0.0969)	(0.0972)						
shibor1									-0.888***	-0.222				
									(0.168)	(0.160)				
shibor7											-0.686***	-0.144		
											(0.142)	(0.132)		
shibor30													-0.572***	-0.137
													(0.104)	(0.101)
Constant	0.0422***	0.000206	0.0561***	0.00567	0.0575***	0.00566	0.0563***	0.00603	0.0558***	0.00550	0.0548***	0.00445	0.0553***	0.00515
	(0.00255)	(0.00208)	(0.00417)	(0.00401)	(0.00417)	(0.00413)	(0.00380)	(0.00381)	(0.00422)	(0.00401)	(0.00440)	(0.00408)	(0.00398)	(0.00386)
Observations	73	73	40	40	40	40	40	40	40	40	40	40	40	40
R-squared	0.086	0.000	0.436	0.052	0.467	0.048	0.489	0.064	0.423	0.048	0.380	0.031	0.442	0.046

Notes: This table shows the regressions of the endogenous component of M2 growth ($EndoMP$) and the exogenous component ($MPshock$) on the required reserve ratio (RRR), interbank pledged repo rates (DR) with 1, 7, 30-day maturities, and Shanghai Interbank Offered Rate (Shibor) with 1, 7, 30-day maturities. The endogenous component of M2 growth captures the systematic reactions of monetary policy to changes in inflation and output growth gaps. The exogenous component of M2 growth is the difference between the actual M2 growth rate and the endogenous component. The numbers in parentheses indicate robust standard errors. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample covers from 2008:Q1 to 2017:Q4.