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

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ABSTRACT. We study the impact of China's 2013 implementation of Basel III on bank risk-taking and its responses to monetary policy shocks using confidential loan-level data from a large Chinese bank. Guided by theory, we use a difference-in-differences (DiD) identification, exploiting cross-sectional differences in lending behaviors between high-risk and low-risk bank branches before and after the new regulations. We identify a novel risk-weighting channel through which changes in regulations significantly reduced bank risk-taking, both on average and conditional on monetary policy easing. However, bank branches reduce risk-taking by increasing lending to ostensibly low-risk state-owned enterprises (SOEs) under government guarantees, despite their low average productivity. Our findings suggest that, under prevailing policies that favor SOEs, China's monetary policy faces a tradeoff between bank risk-taking and 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

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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).

Does monetary policy easing encourage bank risk-taking? In theory, the link between monetary policy and bank risk-taking can be ambiguous. For example, the standard portfolio choice models suggest that, because monetary policy tightening raises the returns on safe assets, it would induce banks to increase their holdings of safe securities and thus reduce risk-taking. Risk-shifting models, however, 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). An increase in deposit interest rates following monetary policy tightening can exacerbate the agency problem. Banks respond to the increase in funding costs by raising the share of lending to riskier borrowers to boost expected returns. In the data, both the portfolio choice considerations and the risk-shifting effects can be present, which makes it challenging to identify the link between monetary policy and bank risk-taking. In general, bank risk-taking can depend on its leverage (Dell'Ariccia et al., 2014). Under limited liability, a more leveraged bank has a greater incentive for risk-taking when it faces an increase in funding costs. Thus, changes in regulations that affect banks' leverage can also affect bank risk-taking and its response to monetary policy shocks.

In this paper, we examine the empirical link between monetary policy and bank risk-taking using Chinese data. We highlight a risk-weighting channel and exploit cross-sectional differences in banks' responses to regulation changes for empirical identification. 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 June 2012, the China Banking Regulatory Commission (CBRC)—China's banking regulator—announced the implementation of the Basel III capital regulations for all 511 commercial banks in China, effective on January 1, 2013. The new capital regulations raised the minimum capital adequacy ratio (CAR) to 10.5% (from 8%).[1] More importantly, the Basel III regulation introduced a new internal ratings-based approach (IRB) that increased the sensitivity of risk-weighted assets to credit risks of bank loans. Under these capital regulations, a bank can boost its effective CAR by either raising its capitalization level or by shifting its assets toward low-risk loans.

To understand the link between bank risk-taking and monetary policy through the risk-weighting channel, we build a theoretical model in which 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 for calculating its CAR is sensitive to loan

[1]For systemically important banks, the minimum CAR was increased to 11.5%.

risks. We obtain several important analytical results from the simple model. First, a binding CAR constraint leads to a negative relation between bank leverage and loan risks. For any given leverage, raising the sensitivity of risk-weighted assets to loan risks reduces bank risk-taking. Second, an expansionary monetary policy shock (e.g., a decline in RR) raises bank leverage, forcing banks to reduce risk-taking. Third, raising the risk-weighting sensitivity amplifies the reduction in bank risk-taking in response to monetary policy easing. Fourth, the responses of bank risk-taking to monetary policy shocks depend on exogenous, bank-specific idiosyncratic risks. Banks facing higher idiosyncratic risks would reduce risk-taking more aggressively following an increase in risk-weighting sensitivity, both on average and conditional on monetary policy easing. We use these theoretical insights to guide empirical identification and we obtain empirical results that are consistent with the model's predictions.

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. 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). We merge the two data sources by matching firm names and obtain about 400,000 unique firm-loan pairs from 2008 to 2017. We use the merged data to estimate the effects of the Basel III implementation on bank risk-taking both on average and conditional on monetary policy shocks. 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).

Guided by theory, we use a difference-in-differences (DiD) identification, exploiting cross-sectional differences in lending behavior between high-risk and low-risk bank branches before and after the implementation of Basel III regulations. In practice, bank branches do not have control over the value of bank capital (the numerator of the CAR), but they do have some control over their risk-weighted assets (the denominator of the CAR). The bank headquarters sets guidelines (or targets) on risk-weighted assets for each branch, and a branch can meet the target by adjusting the quantity of loans or the risk composition of the loans.[2] Thus, cross-sectional variations in the responses of risk-taking between high- and low-risk branches following the implementation of the new regulations help identify the effects of the regulation changes on risk-taking through the risk-weighting channel. In our baseline specification, we measure branch-specific risks by the share of nonperforming loans (NPL) before the Basel III regulations were put in place.

We measure risk-taking based on the credit ratings of loans extended by each branch. Specifically, our measure of risk-taking is a dummy variable that equals one if the loan is rated as AA+ or AAA. The set of independent variables in our empirical specification includes (1) interactions of a dummy variable indicating the periods after the Basel III implementation in 2013 (i.e., a post-regulation dummy) with an indicator of whether a branch had a history of high NPL share before the new regulation (i.e., risk history); and (2) triple interactions between the post-regulation dummy, the risk history indicator, and our measure of monetary policy shocks. We control for year-quarter fixed effects, branch fixed effects, and firm-year fixed effects.

Consistent with theory, we find that, after the Basel III regulations were implemented in 2013, high-risk branches reduced risk-taking relative to low-risk branches by increasing the share of loans with high credit ratings. Risk-taking declined in the post-2013 periods both on average and conditional on monetary policy expansions. The estimated reductions in risk-taking are statistically significant and economically important. Our baseline estimation suggests that, after the new regulations were implemented, a one-standard-deviation positive shock to monetary policy raises the probability of lending to firms with high credit ratings by about 10.68% relative to the sample mean.

We further find that the decline in risk-taking induced by the new capital regulations was driven primarily by changes in risk-weighting sensitivity, not by changes in bank-level capitalization. When we control for the level of capitalization in our regressions, we estimate that the same monetary policy shock raises the probability of lending to firms with high credit ratings by up to 22%, about twice that from the baseline estimation (10.68%).

The main results are robust when we use local competition intensity as a measure of cross-sectional variations (instead of the branch-level risk history). They are also robust to alternative measures of monetary policy shocks, adding controls for loan demand,

[2]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.

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 the transmission of monetary policy to the macroeconomy through a misallocation channel. Under prevailing policies in China, state-owned enterprises (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.[3] Thus, a bank can reduce risk-taking by increasing the share of SOE lending. However, SOEs have lower productivity on average than private firms (Hsieh and Klenow, 2009). 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 exacerbate SOE over-investment and reduce 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 document evidence that, in the post-Basel III periods, monetary policy easing significantly raised the share of SOE lending. The effect is more pronounced for those bank branches with higher NPL ratios before the new regulations. Furthermore, at the province level, monetary policy easing significantly reduces the growth rate of total factor productivity (TFP) after the new regulations but not before. Although SOE loans receive high credit ratings under government guarantees, 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. This finding is consistent with the misallocation channel.

II. Related literature

Our work contributes to the literature on monetary policy transmission through bank risk-taking and credit misallocation.

II.1. **Risk-taking and monetary policy.** Our paper adds to the literature on the bank risk-taking channel of monetary policy transmission. A reduction in the short-term interest rate can boost bank profits and net worth and thus increase the risk-taking capacity (Adrian and Shin, 2010). Monetary policy shocks can also affect the perception and the price of risks and thus change financial institutions' risk-taking behaviors (Borio and Zhu, 2012). Empirical literature has documented some evidence of the risk-taking

[3] Indeed, our evidence suggests that SOE loans receive higher credit ratings on average than non-SOE loans.

channel. Examples include Maddaloni and Peydró (2011), Bruno and Shin (2015), Delis et al. (2017), Bonfim and Soares (2018), and Caglio et al. (2021).

Our model is related to the contribution of Dell'Ariccia et al. (2014), who present a theoretical model to study the effects of changes in the real interest rate on bank risk-taking, highlighting the role of bank leverage. They study a model of financial intermediation, with banks engaging in costly monitoring to reduce the credit risks in their loan portfolios. They show that, under limited liability, a decline in the reference real interest rate reduces the rate the bank has to pay on deposits, alleviating the bank's moral hazard problem and allowing the bank to increase leverage while reducing monitoring efforts. This increases the bank's portfolio risks. In their model, risk-taking is inversely related to bank monitoring efforts. They further show that, when leverage is exogenous, the response of the bank's risk-taking to a real interest rate shock is determined by the balance between risk-shifting and interest rate pass-through, with the net effect depending on the size of the leverage. A reduction in the real interest rate leads highly capitalized banks to reduce monitoring efforts, increasing their portfolio risks.

Similar to Dell'Ariccia et al. (2014), our model also predicts an increase in bank leverage following a reduction in the real interest rate or the required reserve ratio that accompanies monetary policy easing, because the bank's effective funding cost declines. Unlike Dell'Ariccia et al. (2014), however, we explicitly model a bank's joint optimizing decisions of leverage and portfolio risks under capital regulations (in the form of CAR constraints). We show that, since a bank's CAR is evaluated based on risk-weighted assets, a bank's leverage is inversely related to its portfolio risks. A more leveraged bank needs to shift lending to lower-risk borrowers in order to meet the CAR constraint. Thus, different from Dell'Ariccia et al. (2014), whose model abstracts from explicit regulatory policies such as CAR constraints, our model predicts an increase in leverage and a decline in risk-taking following monetary policy easing.

Our paper is also related to the contribution of Coimbra and Rey (2023), who study the risk-taking channel of monetary policy in a dynamic general equilibrium model with heterogeneous financial intermediaries and endogenous entry. They identify a source of time-varying macroeconomic risk that arises from risk-shifting across financial intermediaries. When interest rates are high, reducing interest rates (e.g., following a monetary policy easing) stimulates investment and reduces aggregate risks. In a low interest rate regime, however, reducing interest rates further would benefit the highly leveraged, high risk-taking financial intermediaries. By shifting the distribution of leverage toward high-risk intermediaries, the decline in interest rates increases financial fragility during the boom phase. While Coimbra and Rey (2023) focus on risk-shifting across financial intermediaries, our model highlights the risk-weighting channel stemming from CAR constraints that gives rise to a negative relation between bank leverage and portfolio risks.

Our work complements the empirical literature that highlights the importance of bank capitalization for risk-taking in response to monetary policy shocks. For example, Jiménez et al. (2014) use Spanish loan-level data to show that, following a decline in short-term interest rates, more thinly 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 in bank lending; and this negative relation is stronger for better capitalized banks, reflecting the risk-shifting effect. 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, both on average and conditional on an expansionary monetary policy shock. Importantly, this result is not driven by adjustments in capitalization but by changes in risk-weighting of bank assets. When we control for the level of capitalization, the reduction in risk-taking following a positive monetary policy shock becomes more pronounced.

II.2. **Macroeconomic policies and misallocation.** Our work also adds to the literature that studies the misallocation effects of macroeconomic policies in the presence of credit market distortions.[4]

In an important study, Gopinath et al. (2017) use data for manufacturing firms in Spain between 1999 and 2012 to document a significant increase in productivity losses from capital misallocation over time. They develop a model with financial frictions to show that a decline in the real interest rate associated with the euro convergence process can reduce sectoral TFP as capital inflows are misallocated toward firms with higher net worth but not necessarily higher productivity. Our study highlights the importance of a risk-weighting channel through which monetary policy easing can lead to credit misallocation as banks increase the share of loans to SOEs with higher credit ratings but are not necessarily more productive. In this sense, our work complements that of Gopinath et al. (2017).

[4]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).

Our work is also closely related to Chen et al. (2018), who examine the transmission of monetary policy shocks in the presence of two forms of regulations on bank lending: one imposes a ceiling on the loan-to-deposit ratio (LDR) and the other restricts the quantity of bank loans extended to risky industries such as real estate (i.e., a safe-loan regulation). They exploit the different impacts of these regulations on state vs. non-state banks. They show that a contractionary monetary policy shock increases the risk of deposit withdrawals and tightens the LDR constraints for individual banks. To circumvent the LDR restrictions and the safe-loan regulations, non-state banks shift lending toward off-balance-sheet activities (while state banks are not allowed to bring shadow banking products to their balance sheets), leading to an expansion of unregulated shadow banking.[5] Thus, a contractionary monetary policy shock increases the risk to the banking system through a regulatory arbitrage channel.

Our paper also studies how banking regulations affect a bank's portfolio decisions and risk-taking in response to monetary policy shocks. In line with the findings in Chen et al. (2018), our evidence also suggests that a contractionary monetary policy shock increases bank risk-taking. Unlike their study, we focus on capital regulations (CAR) instead of the LDR ceiling or safe-loan regulations. More importantly, the channels of monetary policy transmission are different. Chen et al. (2018) identify a regulatory arbitrage channel that operates through changes in the composition of lending between on- and off-balance-sheet activities. They assume that on-balance-sheet bank loans are homogeneous and safe, while off-balance-sheet lending is risky. Thus, an increase in the share of off-balance-sheet lending raises the risk to the banking system. In comparison, we abstract from shadow banking while highlighting the importance of heterogeneous credit risks of bank loans. We show that changes in capital regulations have induced important changes in bank risk-taking behaviors in response to monetary policy shocks, because a bank can shift lending between borrowers with different levels of credit risks. In this sense, our study is complementary to the contribution of Chen et al. (2018).

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

III. A static model of bank risk-taking

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

[5]For a related study on the effects of China's banking regulations on shadow banking, see also Hachem and Song (2021).

III.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

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

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.[6]

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

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

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 $\underline{R}\left(\sigma\right)$ and the upper bound $\bar{R}\left(\sigma\right)$ of the distribution $\mathbf{F}(R)$ are respectively given by

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

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

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

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 $\mathbf{E}\left[R\right]$ monotonically increases with the risk parameter σ, implying a risk-return tradeoff, i.e., a higher risk is associated with a higher return. If $\sigma > \sigma^*$, then 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.

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

Each bank has limited liability, such that 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 and the stochastic project return R, and chooses σ, d, and m to solve the profit-maximizing problem

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

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

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

Consistent with the Basel III regulations, the bank's CAR is measured by the ratio of bank capital e to the risk-weighted assets $\xi\left(\sigma\right)k + \xi_m m$, 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.[7] 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.[8] 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

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

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.

[7]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 are increasing with the effective project risk, our assumption on the risk-weighting function is consistent with the IRB approach under Basel III.

[8]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 $\frac{k}{e} = (\frac{k+m}{e} - 1)(1-\theta) + 1$.

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

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

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 $R \geq R^*(\lambda(\sigma))$. 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

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

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.1.1), 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 $\frac{\partial V}{\partial \lambda}\frac{\partial \lambda}{\partial \sigma}$.

The leverage channel depends crucially on the risk sensitivity of the CAR constraint. This makes our model different from the standard models with CAR constraints, such as that studied by Dell'Ariccia et al. (2014). In those standard models, leverage is invariant to project risk (i.e., $\frac{\partial \lambda}{\partial \sigma} = 0$). Thus, the indirect effect of project risk on bank profit through its effects on leverage is 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 Proposition 1.

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

$$\frac{\partial\sigma}{\partial\psi}<0, \quad \frac{\partial\sigma}{\partial\rho}<0. \tag{17}$$

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. See Appendix S.1. □

Given the CAR constraint, an expansionary monetary policy (i.e., a decline in θ) induces the bank to increase its leverage and to reduce risk exposures σ. 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 2.[9]

[9] 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 2.

Proposition 2. 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,

$$\frac{\partial \lambda}{\partial \theta} < 0, \quad \frac{\partial \sigma}{\partial \theta} > 0. \tag{18}$$

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 led to an increase in the required bank capitalization, corresponding to an increase in ψ in our model. The new regulations also 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.

As shown in Proposition 2, monetary policy easing (i.e., a reduction in θ) raises bank leverage and reduces risk-taking under given capital regulations (parameterized by ψ and ρ). 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. In a regime with a higher ρ, however, the bank's leverage and capitalization level would become more sensitive to project risks. Thus, monetary policy easing would lead to a larger reduction in risk-taking. These implications depend crucially on the negative relationship between leverage and optimal project risk under a binding CAR constraint (i.e., $\frac{\partial \lambda}{\partial \sigma} = -\frac{\rho}{\psi \sigma^{\rho+1}} < 0$). These results are formally stated in Proposition 3.

Proposition 3. 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, and it increases with the risk-weighting sensitivity ρ. In particular, we have

$$\frac{\partial^2 \sigma}{\partial \theta \partial \psi} < 0, \quad \frac{\partial^2 \sigma}{\partial \theta \partial \rho} > 0. \tag{19}$$

Proof. See Appendix S.1. □

We provide a graphical illustration in the online appendix, illustrating how capital regulations under Basel III could affect bank risk-taking and its response to a monetary policy shock.

III.2. **Banks' idiosyncratic risks.** For empirical identification, we need cross-sectional heterogeneity. For this purpose, we extend our baseline theoretical model by introducing idiosyncratic risks facing banks. 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.[10]

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.

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

$$\frac{e}{\xi(\sigma\Delta)k} \geq \tilde{\psi}, \tag{20}$$

where $\xi(\sigma\Delta)$ denotes the risk-weighting function (after imposing a zero risk weight on reserves). We parameterize the risk-weighting function such that $\xi(\sigma\Delta) = \mu(\sigma\Delta)^{\rho}$, 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 decisions implies that

$$\frac{1+\rho}{2\sigma}\left[\bar{R}(\sigma) - R^*(\sigma)\right] = \frac{\partial\left[\bar{R}(\sigma) - R^*(\sigma)\right]}{\partial\sigma} + \frac{1-\rho}{4}\left[(\Delta-1) - \frac{2}{\sigma}r\psi\sigma^{\rho}(\Delta^{\rho}-1)\right], \tag{21}$$

where $\bar{R}(\sigma)$ and $R^*(\sigma)$ are the upper bound of R and the threshold of insolvency when $\Delta = 1$. Eq. (21) shows that the model with bank-specific idiosyncratic risks nests the baseline model in the special case with $\Delta = 1$. The second term on 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,

[10]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.

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. (21) 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 4.

Proposition 4. 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 3, 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 5.

Proposition 5. 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,

$$\frac{\partial^2\sigma}{\partial\rho\partial\Delta} < 0. \tag{22}$$

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

$$\frac{\partial}{\partial\Delta}\left[\frac{\partial\sigma}{\partial\theta}|_{\rho=1} - \frac{\partial\sigma}{\partial\theta}|_{\rho=0}\right] > 0. \tag{23}$$

Proof. See Appendix S.1. □

IV. Empirical analysis

The theoretical model predicts that increasing risk-weighting sensitivity reduces bank risk-taking, and that banks facing higher idiosyncratic risks reduce risk-taking more aggressively. The model also predicts that an expansionary monetary policy shock raises bank leverage, forcing banks to reduce risk-taking under binding CAR constraints. Increasing the risk-weighting sensitivity amplifies the reduction in bank risk-taking in response to monetary policy easing, 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.

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

IV.1.1. *The data.* We construct a unique micro data set using confidential loan-level data from one of the Big Five commercial banks in China, merged with firm-level data in China's Annual Survey of Industrial Firms (ASIF).[11] 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.[12] 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 name), 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 consistent firm identification code, we merge the loan data with the firm data using firm names. The merged data set contains information on about 400,000 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.

IV.1.2. *Changes in banking regulations and bank risk-taking.* The Basel III regulations implemented in early 2013 raised the minimum CAR from 8% to 10.5%. It has also introduced the IRB approach for evaluating bank asset risk based on loan default probabilities and default exposures.[13]

[11]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 China Banking Regulatory Commission, in our sample period from 2007 to 2017, the Big Five banks accounted for approximately half of the total loans in the banking sector.

[12]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).

[13]The CBRC formally approved the Big Five commercial banks' applications for adopting the IRB approach to assess risk-weighted assets in April 2014. The banks had prepared for the implementation of the IRB approach well before the formal approval date. For instance, in the 2012 annual report of the Industrial and Commercial Bank of China (ICBC), the bank explicitly stated in the section *Preparation for the implementation of capital regulation* that "In respect of credit risk, the Bank further ... reinforced

Our theory in Section III predicts that the increased sensitivity to risk-weighting under the new Basel III regulations should reduce bank risk-taking. Figure 1 presents some suggestive evidence that banks have reduced risk weights on their assets by shifting lending to low-risk borrowers in the post-2013 period. The figure shows that the share of high-rating loans (i.e., those loans rated AAA or AA+) declined steadily from 2008 to 2012, but it has been increasing since 2013. Formal tests of structural breaks (such as the Bai-Perron test) identifies a structural break in the share of loans rated AA+ or AAA in the first quarter of 2013,[14] suggesting that the changes in capital regulations have contributed to changes in bank risk-taking.[15]

IV.2. **The empirical model and the estimation approach.** We now examine formally 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

$$\begin{aligned} HighR_{ijdt} &= \alpha \times RiskH_j \times Post_y + \beta \times RiskH_j \times Post_y \times MP_t \\ &+ \gamma \times RiskH_j \times MP_t + \theta \times X_i \times \mu_y + \eta_j + \mu_t + \zeta_d + \epsilon_{ijdt}. \end{aligned} \tag{24}$$

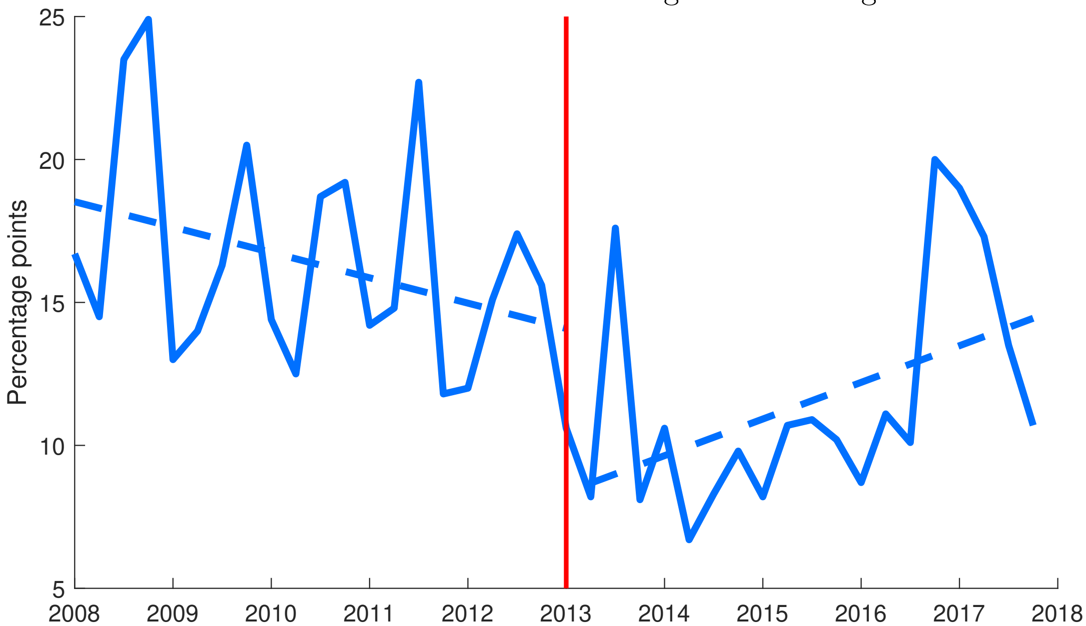
In this specification, the dependent variable $HighR_{ijdt}$ is a dummy variable indicating whether the loan has a high credit rating (AA+ or AAA). Specifically, the dummy variable takes a value of one if loan i issued by city-level branch j in industry d and quarter t is rated as AA+ or AAA, and zero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

the group management of *the internal rating of credit risks*. It pushed forward the optimization of the internal rating system and model and constantly improved the business verification system of internal rating business. Besides, the Bank continuously promoted the application of *internal rating* results in credit approval, risk monitoring and early warning, risk limit setting, economic capital measurement and performance appraisal." In the 2013 annual report, the ICBC stated in the section *Credit Risks* that "The Bank also continuously advanced the application of *internal rating* results, and accelerated the construction of credit risk monitoring and analysis center to enhance the whole process monitoring and supervision of credit risk. As a result, credit risk management of the Bank was fully strengthened." See the Appendix for additional details of changes in China's bank regulation policy.

[14]We implement Bai-Perron (BP) multiple breakpoint tests on the time series of the share of high-rating loans to detect potential breaks. The BP test identifies a statistically significant break point of 2013:Q1. The BP test with global information criterion (LWZ) also selects one break at the date of 2013:Q1.

[15]In practice, the CAR constraints are not always binding. However, as we show in the Appendix (see Figure A.1), the Big Five Chinese commercial banks responded to the implementation of the Basel III regulations that raised the minimum CAR by increasing their effective CAR. Our theory suggests that, to the extent that banks would like to maintain a buffer between their effective CAR and the regulatory minimum, changes in capital regulations should have impact on banks' risk-taking behaviors.

Figure 1. Share of loans with high credit ratings



Notes: This figure shows the quarterly time series of the share (in percentage points) of loans with high credit ratings (i.e., those rated AA+ or AAA) in total loans. The dashed lines are the linear fitted trends for the time series before and after 2013. The Bai-Perron test detects a significant structural trend break in 2013:Q1.

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 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 quantity of loans or the risk-composition of the loans.[16] 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 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.

[16]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."

Our theoretical model suggests that the impact of changing the sensitivity to risk-weighting on bank risk-taking can vary across bank branches, depending on their idiosyncratic risks (see Proposition 5). In particular, high-risk bank branches should be more sensitive to regulatory changes than low-risk branches. Based on this theoretical implication, 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. Our theory suggests that a bank branch with a higher level of idiosyncratic risks would take more risks in lending (see Proposition 1), resulting in a higher average share of nonperforming loans. In our empirical specification (24), we include the interaction term $RiskH_j \times Post_y$ to capture the relative responses of the high-risk branches to changes in the regulations. Our theory suggests that the coefficient on this interaction term should be positive (i.e., $\alpha > 0$).

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 1 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.

To examine how changes in banking regulations could affect the responses of risk-taking following monetary policy shocks, we construct a measure of monetary policy shocks (i.e., the term MP_t in Eq. (24)) based on an estimated M2 growth rule using the regime-switching approach of Chen et al. (2018). The monetary policy shock is the exogenous component of M2 growth, which equals the difference between actual M2 growth and the component representing systematic reactions to the state of the economy. 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

Table 1. 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	0.269	0.297	-0.028	-0.824	0.410
AAA&AA+ loan share	0.097	0.072	0.025	1.206	0.229
Small firm loan share	0.218	0.193	0.025	1.162	0.246
Average loan rate (%)	6.274	6.299	-0.025	-0.663	0.508
log(interest income)	17.001	17.023	-0.021	-0.136	0.892
log(loan amount)	19.779	19.796	-0.017	-0.108	0.914
Loan-to-firm asset ratio	0.142	0.130	0.012	0.546	0.586

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 share, high-rating (AAA or AA+) loan 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.

the RR ratio, the repo rates, and the Shibor rates, suggesting that it captures exogenous shocks to China's monetary policy.[17]

Our theory predicts that, under given CAR regulations, monetary policy easing reduces bank risk-taking (Proposition 2); raising the sensitivity to risk-weighting amplifies the reduction in risk-taking following a monetary policy expansion (Proposition 3); and furthermore, the reductions in risk-taking following an expansionary monetary policy shock should be more pronounced for branches with higher idiosyncratic risks (Proposition 5). To capture these effects, we include the triple interaction term $RiskH_j \times Post_y \times MP_t$

[17]See Online Appendix S.2.1.

in our empirical specification. Our theory predicts that the coefficient on this triple interaction term should be positive (i.e., $\beta > 0$).[18]

The variable X_i in Eq. (24) is a vector of control variables for the initial conditions facing firm i (i.e., the borrower of loan i). It includes firm characteristics such as the size (measured by the log of total assets), the age, the leverage, and the returns on assets (ROA). We do not have data on these firm characteristics after 2013, since the ASIF sample covers the period from 1998 to 2013. To capture potential time variations of firm characteristics, we follow Barrot (2016) and include interactions between the initial conditions X_i with the year fixed effect μ_y.[19] The set of independent variables also includes city (or equivalently, branch) fixed effect η_j, time (quarters) fixed effect μ_t, and industry fixed effect ζ_d. Finally, the term ϵ_{ijdt} denotes the regression residual.[20] The parameter γ in Eq. (24) measures the average response of bank risk-taking to monetary policy shocks in the full sample. Our theory predicts that, under the new regulations (i.e, in the post-2013 period), an expansionary monetary policy should raise bank leverage and reduce risk-taking (see Proposition 2). Before introducing the IRB approach in 2013, however, banks could not choose the risk weights on their corporate loans based on credit risk. Thus, our theory has no clear predictions for the sign of γ.

Table 2 displays the summary statistics for the variables of interest in our analysis. The mean probability of high-rating lending (the $HighR$ dummy) is 4.1% with a standard deviation of about 0.2. The average share of high-risk branches (the $RiskH$ dummy) before 2013 is about 51.5%, with a standard deviation of 0.5. The monetary policy shock (MP) has a mean of zero and a standard deviation of 0.007.

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

IV.3.1. *Baseline estimation results.* Table 3 reports the estimation results from the baseline empirical model in Eq. (24). Column (1) shows the ordinary least squares (OLS) estimation results. Consistent with theory, the estimated values of α and β are both

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[18]Under the empirical specification (24), 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.

[19]One advantage of this approach is that the interaction term is exogenous to changes in banking regulations after 2013.

[20]In the empirical specification (24), 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.

TABLE 2. Summary statistics

Variables	Obs.	Mean	Std	Min	Median	Max
$HighR$	264,213	0.041	0.197	0.000	0.000	1.000
$RiskH$	365,684	0.515	0.500	0.000	1.000	1.000
MP	365,724	0.000	0.007	-0.017	0.001	0.027

positive and statistically significant.[21] The positive value of α suggests that, after implementing Basel III, bank branches (especially those with risky balance sheets in the past) reduced their risk exposure by shifting lending to high-rating loans relative to the pre-2013 period. The positive value of β implies that, following an expansionary monetary policy shock, bank branches with a high initial NPL ratio shifted more lending toward high-rating loans in the post-2013 periods relative to before. The estimated value of γ is significantly negative, indicating that an expansionary monetary policy shock by itself increases risk-taking on average. We obtain similar results when we estimate a probit model instead of an OLS model (see Column (2) of the table).[22]

The point estimate of $\beta = 0.896$ implies that, for those bank branches with a high NPL ratio in the past, a one-standard-deviation increase in the monetary policy shock (0.7%) would raise the probability of lending to firms with high credit ratings by $0.896 \times 0.7\% = 0.63\%$, an increase of about 10.68% relative to the mean (the sample mean of the share of high-rating loans is 5.9%). In this sense, our estimated effects of monetary policy shocks on bank risk-taking under the new capital regulations are not just statistically significant but also economically important.

IV.3.2. *Capitalization or risk-weighting?* The literature shows that the relation between bank risk-taking and monetary policy depends on the level of capitalization (Jiménez et al., 2014; Dell'Ariccia et al., 2017). Our theory suggests that changes in the risk-weighting sensitivity can also affect risk-taking in response to monetary policy shocks (Propositions 3 and 5).

The implementation of Basel III in 2013 raised the required CAR from 8% to 10.5%. It also introduced the new IRB approach for calculating risk-weighted assets, increasing

[21]We report robust standard errors in the baseline regressions. Clustering the standard errors by firms or by bank branches does not affect the main results, as we discuss in Supplementary Appendix C.

[22]The variables used in our estimation are not demeaned. Thus, in general, the estimated coefficient α for the interaction term $RiskH_j \times Post_y$ may not capture the average effect but the effect for the periods when $MP_t = 0$. This concern, however, is not important in practice because the monetary policy shock MP_t has a mean of zero (see Table 2).

Table 3. Effects of regulations on bank risk-taking

	(1)	(2)	(3)	(4)
	$HighR$	$HighR$	$HighR$	$HighR$
	OLS	probit	OLS	probit
$RiskH_j \times MP_t \times Post_y$	0.8962***	0.8186***	1.8431***	1.7275***
	(0.1995)	(0.2371)	(0.3216)	(0.3829)
$RiskH_j \times Post_y$	0.0064***	0.0087***	0.0038**	0.0063**
	(0.0013)	(0.0017)	(0.0019)	(0.0026)
$RiskH_j \times MP_t$	-0.7143***	-0.4893***	7.9610***	8.1918***
	(0.1708)	(0.1633)	(2.1437)	(2.8515)
$RiskH_j \times MP_t \times CAR_{y-1}$			-0.6862**	-0.6841***
			(0.1707)	(0.2247)
$RiskH_j \times CAR_{y-1}$			0.0015	0.0015
			(0.0009)	(0.0013)
Branch FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial controls $\times$ year FE	yes	yes	yes	yes
R^2	0.194		0.194	
Observations	212,631	141,498	212,631	141,498

Notes: This table reports the estimation results in the baseline model. $HighR$ is equal to 1 if and only if the rating of the loan is AA+ or AAA. Columns (1), (3) and Columns (2), (4) use OLS and probit models, respectively. The monetary policy shock is constructed using the approach in Chen et al. (2018). The CAR for the pre-2013 period is measured using the traditional RW approach, and for the post-2013 period, it is measured using the IRB approach. Both 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, 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.

the sensitivity of risk-weighting to credit risks. To isolate the effects of changes in risk-weighting sensitivity on the risk-taking channel of monetary policy shocks, we augment our baseline empirical specification (24) by including two additional controls for the effects of capitalization—a one-year lag of the effective CAR of the bank (CAR_{y-1}) and its interaction with the monetary policy shock ($MP_t \times CAR_{y-1}$)—both interacted with the risk history ($RiskH_j$). Since the CAR calculation methods changed in 2013, we construct a measure of the effective CAR based on the RW approach for the pre-2013 period, and then splice it with the CAR calculated based on the new IRB approach for the post-2013 period.

Table 3 reports the estimation results after controlling for the effects of capitalization (Columns (3) and (4)). In both the OLS and the probit regressions, the estimates of the coefficient on $RiskH_j \times MP_t \times CAR_{y-1}$ are significantly negative, implying that better capitalization leads to more risk-taking following an expansionary monetary policy shock. This result is consistent with that obtained by Dell'Ariccia et al. (2017) using U.S. data.

After controlling for the effects of capitalization, the estimated coefficient on $RiskH_j \times MP_t \times Post_y$ remains significantly positive, with a magnitude about twice as large as that in baseline regression. For example, under the OLS specification in Column (3), the point estimate rises from the baseline value of 0.896 to 1.843.[23] The point estimate (1.843) implies that a one-standard-deviation monetary policy shock would increase the probability of SOE lending by about 22% (relative to the mean). We obtain similar results when we estimate the probit model (see Column (4)).[24] These results suggest that the declines in bank risk-taking following a monetary policy expansion in the post-2013 period were driven primarily by changes in the risk-weighting sensitivity, not by changes in bank-level capitalization.

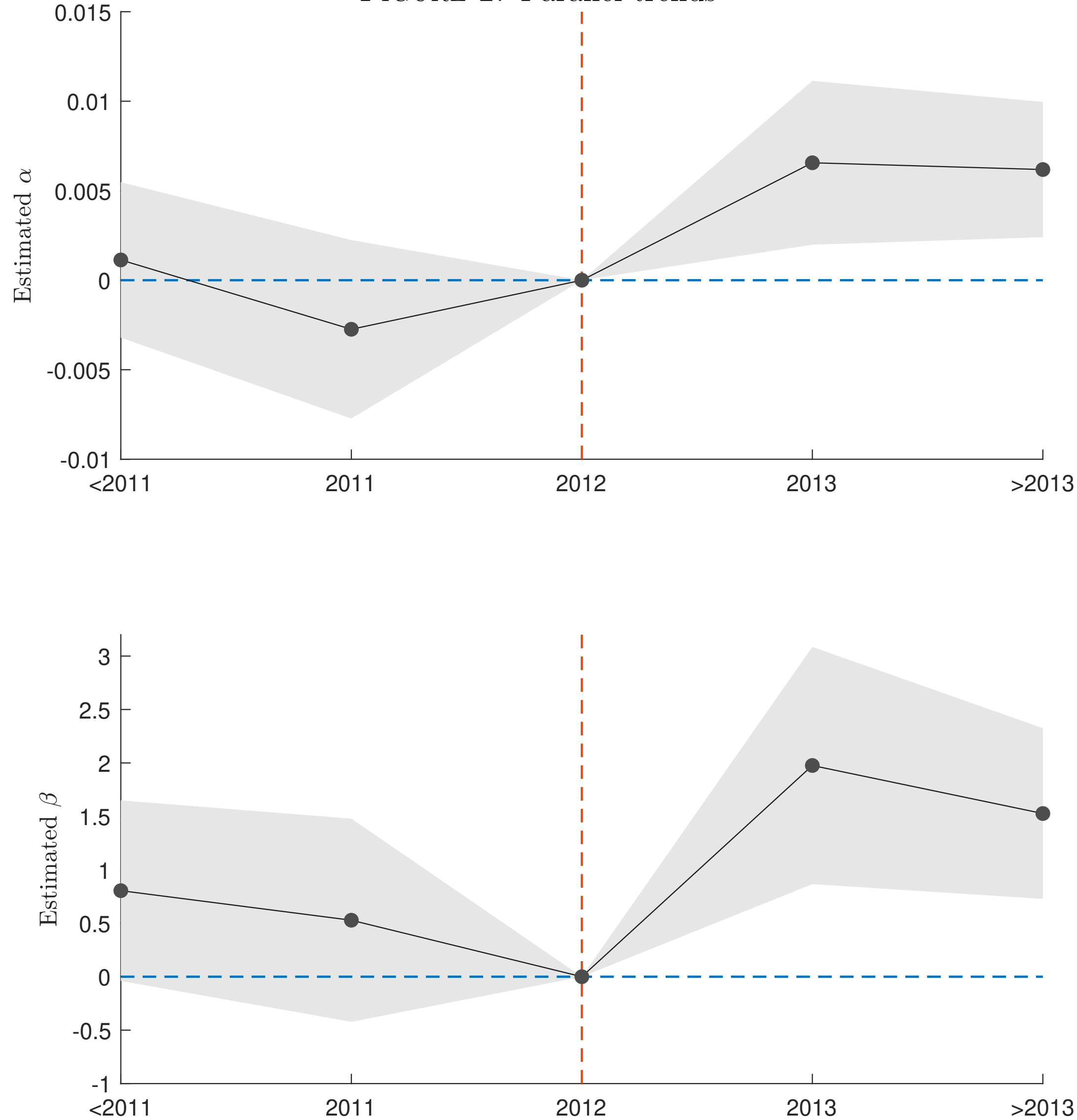
IV.3.3. *Parallel trends.* Our difference-in-difference identification assumes that the risk-taking behaviors of the treatment group (i.e., the high-risk branches) and the control group (i.e., the low-risk branches) followed parallel trends in the pre-2013 period, but diverged after the new regulations were put in place.

To examine the validity of our parallel trends identification assumption, we separately estimate the dynamic impact of the risk-taking behavior of the treatment group (α) and

[23]The effective CAR is endogenous and can be correlated with the $Post_y$ dummy. This correlation, however, does not change the consistency of the point estimates of the coefficients on $RiskH_j \times Post_y$ and $RiskH_j \times MP_t \times Post_y$, although it might affect the standard errors.

[24]We have also estimated the same model by replacing the CAR measure with the deviations of the effective CAR from the required CAR (i.e., a CAR gap), or by including both the effective CAR and the CAR gap. The results are similar.

FIGURE 2. Parallel trends



Notes: The figure shows the estimated time-varying coefficients α and β for the years before 2011, 2011, 2013, and after 2013 from the empirical model. The dots indicate the point estimates, and the shaded gray areas indicate the 95% confidence bands. The treatment group consists of the high-risk bank branches with average NPL ratios above the median in the pre-2013 period. The control group consists of the low-risk branches with pre-2013 average NPL ratios below the median. The coefficient α_τ measures the difference in the share of SOE lending between the treatment group and the control group in year τ. The coefficient β_τ measures the difference in SOE lending between these two groups conditional on monetary policy shocks. We use 2012 as a reference year.

the response of risk-taking to a monetary policy shock for the treatment group (β), by replacing the variable $Post_y$ with a series of time 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.[25]

Figure 2 shows the point estimates along with the 95% confidence bands. The figure shows that, in the pre-2013 period, the estimated values of α and β are insignificantly different from zero, implying that the risk-taking behaviors of the treatment group—both on average and conditional on monetary policy shocks—were not significantly different from those of the control group. The figure also shows that, since the regulation was implemented (2013 and after), the estimated values of α and β both turned positive and statistically significant at the 95% confidence level, implying significant reductions in risk-taking by the high-risk branches (relative to the low-risk branches). These results suggest that the shock (i.e., the implementation of Basel III) triggered changes in the behaviors of the treatment group relative to the control group, validating our identification assumption.

IV.4. **Robustness of Empirical Analysis.** Our baseline estimation results are robust to alternative identification, measurements, model specifications, and additional controls.

IV.4.1. *Alternative identification of the risk-taking channel.* In our baseline regression, we identify the effects of changes in regulatory and monetary policies on bank risk-taking using cross-sectional variations in the risk history of bank branches. We now show that the results are robust when we identify the risk-taking channel using cross-sectional variations in local loan market competition.

To provide a theoretical underpinning for this alternative identification approach, we extend the baseline theoretical model to incorporate local banking competition.[26] In the model, an increase in market power reduces the sensitivity of bank leverage to changes in regulatory policy and monetary policy. Thus, 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.[27]

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

[26]For details of the model, see Appendix B.

[27]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

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.[28]

Table 4 reports the estimation results. Column (1) shows the OLS estimation results. The estimated coefficients on both $LocalComp_k \times Post_y$ and $LocalComp_k \times MP_t \times Post_y$ are significantly positive, consistent with the theory's predictions. Specifically, the positive coefficient of the term $LocalComp_k \times Post_y$ indicates that, after the implementation of Basel III, a subbranch facing stronger local competition shifts lending to firms with higher credit ratings relative to the pre-2013 period. The positive coefficient of the triple interaction term $LocalComp_k \times MP_t \times Post_y$ suggests that, under the new capital regulations, monetary policy easing increased the share of lending to firms with high credit ratings, especially for those subbranches facing more intense local competition. The results are similar when we estimate the model using probit regression (Column 2). Interestingly, the negative and significant estimated coefficient of $LocalComp_k$ indicates that, on average (i.e., absent changes in regulatory policy or monetary policy), more intense local competition leads to more risk-taking. These results suggest that implementing the Basel III capital regulations has significantly altered the relation between local bank competition and risk-taking.

Similar to what we find in the baseline regressions, the observed effects of capital regulations and monetary policy shocks on risk-taking depend mainly on changes in the risk-weighting sensitivity, not on the level of capitalization. As shown in Columns (3) and (4) of Table 4, the effects of regulatory policy changes and monetary policy easing on risk-taking remain positive and significant when we add controls for the effects of lagged capitalization.

IV.4.2. *Controlling for loan demand factors.* A potential concern of our baseline regression is that increases in high-rating lending in the post-2013 period might be driven by

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).

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

Table 4. Effects of regulations on bank risk-taking: Local competition

	(1)	(2)	(3)	(4)
	$HighR$	$HighR$	$HighR$	$HighR$
	OLS	probit	OLS	probit
$LocalComp_k \times MP_t \times Post_y$	0.4417***	0.4820***	0.5555***	0.6706***
	(0.1281)	(0.1284)	(0.1994)	(0.2032)
$LocalComp_k \times Post_y$	0.0033***	0.0070***	0.0018	0.0052***
	(0.0009)	(0.0010)	(0.0012)	(0.0015)
$LocalComp_k \times MP_t$	-0.2380**	-0.1332	0.6856	1.5026
	(0.1077)	(0.0858)	(1.4128)	(1.5977)
$LocalComp_k$	-0.0016**	-0.0067***	-0.0155**	-0.0228**
	(0.0007)	(0.0007)	(0.0077)	(0.0095)
$LocalComp_k \times MP_t \times CAR_{y-1}$			-0.0726	-0.1287
			(0.1115)	(0.1256)
$LocalComp_k \times CAR_{y-1}$			0.0011*	0.0013*
			(0.0006)	(0.0008)
Branch FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes
R^2	0.197		0.197	
Observations	201,527	130,662	201,527	130,662

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 in the 5 km around the subbranch k in our sample. $HighR$ is equal to 1 if and only if the rating of the loan is AA+ or AAA. The monetary policy shock is constructed using the approach in Chen et al. (2018). The CAR is the same as baseline model. Margins are reported for the probit models. All models include controls for the branch fixed effects, the industry fixed effects, and the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, 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 5. Effects of regulations on bank's risk-taking: controlling for time-varying borrower characteristics

	(1) *LoanRateGap*	(2) *LoanRateGap*
$RiskH_j \times HighR_{it} \times MP_t \times Post_y$	-10.4252***	-10.7132***
	(3.4827)	(3.5449)
$RiskH_j \times MP_t \times Post_y$	-0.9838	-0.9432
	(1.0541)	(1.0491)
$RiskH_j \times MP_t$	-0.0649	-0.0918
	(0.5815)	(0.5823)
$RiskH_j \times HighR_{it} \times MP_t$	1.3242	1.2345
	(1.1957)	(1.1851)
$RiskH_j \times HighR_{it}$	0.0615***	0.0627***
	(0.0184)	(0.0188)
$RiskH_j \times HighR_{it} \times Post_y$	-0.1576***	-0.1654***
	(0.0432)	(0.0443)
$\log(LoanAmount_{ijt})$		-0.0007***
		(0.0002)
Branch $\times$ post FE	yes	yes
Branch $\times$ month FE	yes	yes
Firm-year-quarter FE	yes	yes
R^2	0.931	0.931
Observations	199,430	198,883

Notes: This table reports the estimation results by controlling demand factors. *LoanRateGap* is the percentage deviations of the individual loan rate *LoanRate* from the benchmark loan rate, where *LoanRate* is the loan interest rate (in %) on each loan. The monetary policy shock is constructed using the approach in Chen et al. (2018). Both models include controls for time-varying borrower's characteristics through the firm-year-quarter fixed effects. We also include controls for the branch $\times$ post fixed effects and branch $\times$ month fixed effects. Other fixed effects in the baseline model such as branch, industry, year-quarter and initial control $\times$ year fixed effects are absorbed by the controls in the current regression. The numbers in the parentheses indicate robust standard errors. 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.

changes in loan demand of firms with high credit ratings (relative to those with low credit ratings), instead of changes in banks' credit supply decisions in response to the new regulations.

To address this concern, we control for time-varying borrower characteristics to isolate the effects of the policy changes through the credit supply channel. To implement this, we follow the approach of Khwaja and Mian (2008) and restrict our sample to those firms that borrow from multiple bank branches. The dependent variable (denoted by $LoanRateGap_{ijt}$) is the firm-specific loan interest rate (measured as the percentage deviation from the benchmark loan rate) offered to firm i by branch j in quarter t. We are interested in estimating the differential impacts of changes in regulatory policy and monetary policy on the loan rates offered to firms with high vs. low credit ratings in the post-2013 periods. We use a similar DiD identification approach to that in the baseline model, exploiting the differences in the loan rates offered by high-risk vs. low-risk bank branches. This effect is captured by the coefficient on the quadruple interaction term $RiskH_j \times HighR_{it} \times MP_t \times Post_y$. Here, 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 variables are the same as defined in the baseline regression (24). We control for potentially time-varying demand factors by including a firm-year-quarter fixed effect in the regression.

Table 5 displays the regression results. Column (1) shows that, controlling for the firm-year-quarter fixed effects, an expansionary monetary policy shock in the post-2013 period leads to a significant decline in the relative loan interest rate offered by a high-risk branch to firms with high credit ratings (i.e., a negative coefficient on the quadruple interaction term). The point estimate implies that a positive one-standard-deviation monetary policy shock (0.7%) reduces the loan rate for firms with high credit ratings (relative to those with low ratings) by about 7.3 basis points ($-10.43 \times 0.007 \approx -0.073$). The same monetary policy shock has no significant impact on the loan rate for firms with low credit ratings (i.e., an insignificant coefficient on $RiskH_j \times MP_t \times Post_y$). In comparison, in the pre-2013 period, an expansionary monetary policy shock had no significant impact on the loan rate, regardless of the firms' credit ratings (i.e., the coefficients on both $RiskH_j \times HighR_{it} \times MP_t$ and $RiskH_j \times MP_t$ are insignificant). These results suggest that, with increased risk-weighting sensitivity under the new regulations, bank lending behaviors have changed significantly following a monetary policy shock. Consistent with our baseline finding, monetary policy easing in the post-2013 period reduced bank risk-taking because bank lending favors firms with high credit ratings. The evidence here also suggests that the new capital regulations reduced risk-taking even in the absence of monetary policy shocks. Specifically, the estimated coefficient on the triple interaction term $RiskH_j \times HighR_{it} \times Post_y$ is significantly negative, indicating that a high-risk branch charged a lower loan rate to firms with high credit ratings than those with low ratings in the post-2013 period. These empirical patterns are robust to controlling for the loan amount, as shown in Column (2).

The difference between the pre- and post-2013 lending behaviors confirms our baseline finding that, under the new capital regulations, high-risk branches shifted lending to high-rating firms following an expansionary monetary policy shock. Since we have controlled for time-varying borrower characteristics, the observed changes in lending behavior cannot be explained by changes in demand conditions; they are more likely driven by changes in credit supply decisions under the new regulations.

IV.4.3. *Further robustness checks.* Our main empirical results are robust to alternative measurements, specifications, and controls. In particular, the results remain valid when we consider (1) measuring monetary policy shocks based on an interest rate rule, (2) controlling for the effects of interest rate liberalization, (3) controlling for the effects of the deleveraging policy, (4) controlling for the effects of the anti-corruption campaign, (5) adding more controls in the baseline regressions, (6) clustering the standard errors at the bank branch and year-quarter levels instead of computing robust standard errors, (7) using alternative measures of risk history, or (8) using data from multiple banks. To conserve space, we report those results in Appendix C.

V. Risk-taking and misallocation

China's prevailing government policy favors SOEs that are ostensibly safer borrowers but have lower average productivity than private firms. Thus, shifting lending to SOEs can reduce loan risks, but it can also lead to credit misallocation that lowers aggregate productivity. We now document evidence of the misallocation effects of monetary policy shocks through the risk-weighting channel under the Basel III regulations.

V.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.[29]

The positive correlation between high-rating loans and SOE lending prevails when we control for time and location fixed effects and firm characteristics. Table 6 shows

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

TABLE 6. Credit ratings and SOE loans

	(1)	(2)	(3)	(4)
Credit Rating	OLS	Ordered probit	Ordered probit	Ordered probit
SOE	1.3788***	0.8837***	0.5203***	0.5630***
	(0.0318)	(0.0080)	(0.0118)	(0.0134)
Branch FE	yes	no	no	yes
Year-quarter FE	yes	no	yes	yes
Initial controls × year FE	yes	no	yes	yes
R^2	0.223	–	–	–
Observations	232,073	264,213	232,073	232,073

Notes: Column (1) reports the results in OLS estimation. Columns (2)-(4) report results in ordered probit estimation. Initial controls include the average firm characteristics (including size, age, leverage, and ROA) in the years before 2013. The numbers in parentheses are robust standard errors. The statistical significance is denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

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 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.

V.2. **Effects of policy changes on SOE lending and credit allocation.** The positive relation between SOE loans and high credit ratings suggests that a bank branch can reduce risk-taking in the post-2013 period by shifting lending to SOE firms in response to an expansionary monetary policy shock. We now examine the empirical relevance of this credit reallocation channel.

For this purpose, we re-estimate the baseline specification (24) with the dependent variable replaced by the SOE dummy. Table 7 reports the estimation results from OLS (Column (1)) and probit (Column (2)). The estimated coefficient on the triple interaction term $RiskH_j \times MP_t \times Post_y$ is positive and significant, 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, suggest 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 and 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 $\log MPK$) is the logarithm of the mean of the average product of capital of a given firm over the period from 2010 to 2012, prior to the implementation of Basel III in China. The set of independent variables is the same as in the baseline.

Table 7 (Column (3)) 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.[30] This finding suggests that, under the new capital regulations, monetary policy easing can lead to credit misallocation through the risk-weighting channel.

To further identify the channel effects of SOE lending on the 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 (1) of Table 7). This regression helps isolate the changes in SOE lending caused by changes in regulatory policy ($RiskH_j \times Post_y$) and the joint changes in regulatory and monetary policies ($RiskH_j \times MP_t \times Post_y$). The second-stage regression estimates the relationship between firm-level MPK over the initial years (pre-2013) and the predicted SOE lending from the first stage. This two-stage approach is formally identically to an instrumental-variable estimation where policy changes (captured by the two interaction terms in the first stage) are used as instruments for SOE lending.

We report the two-stage estimation results in Columns (4) and (5) of Table 7. In the first-stage regression (Column (4)), the coefficient on the triple interaction term ($RiskH_j \times MP_t \times Post_y$) is positive and significant at the 99% level, consistent with

[30] Since the dependent variable $\log MPK$ is a continuous variable (instead of a dummy indicator), we report the OLS regression results only.

Table 7. Effects of regulations on SOE lending and credit allocation

	(1)	(2)	(3)	(4)	(5)
	SOE	SOE	$\log MPK$	SOE	$\log MPK$
	OLS	probit	OLS	First-stage	Second-stage
$RiskH_j \times MP_t \times Post_y$	0.6860***	0.6079***	-2.1074*	0.6065***	
	(0.1953)	(0.1830)	(1.1488)	(0.2037)	
$RiskH_j \times Post_y$	0.0016	0.0046***	-0.0107	0.0014	
	(0.0014)	(0.0014)	(0.0083)	(0.0014)	
$RiskH_j \times MP_t$	-0.2181	-0.1843	1.0645	-0.1824	
	(0.1554)	(0.1155)	(0.8340)	(0.1610)	
$\widehat{SOE}_{ijt}$					-3.2614*
					(1.9078)
Branch FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes	yes
R^2	0.366		0.207		
Observations	293,603	265,134	260,329	260,329	260,329

Notes: This table reports the estimation results on SOEs and marginal product of capital. $\log MPK$ is the logarithm of the mean of the average product of capital (APK) ratio from 2010 to 2012. APK is measured by the value added 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, industry fixed effects, year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, and ROA) in the years before 2013 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.

the baseline results reported in Column (1).[31] In the second stage, we regress $\log MPK$ on the predicted SOE from the first stage. As shown in Column (5), the coefficient is negative and significant at the 90% level. Thus, an increase in SOE lending caused by changes in regulatory and monetary policies is associated with lower MPK. These results

[31] 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.

suggest that SOE lending is a crucial channel through which monetary policy shocks can lead to credit reallocation and potential misallocation.

In Appendix D, we present further evidence of the misallocation effects of monetary policy shocks under the new capital regulation. 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 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.

V.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. We now examine the ex post performance of SOE loans.

We measure the ex post loan performance by the share of overdue loans. Table 8 shows that, without controls for credit ratings, an SOE loan is less likely to be overdue, consistent with the evidence that SOE loans on average receive high credit ratings. However, when we control for credit ratings, SOE loans are more likely to become overdue, suggesting that their ex post performance is worse than that of non-SOE loans within the same category of credit ratings. This finding suggests that, while raising the share of SOE lending helps a branch reduce risk-weighted assets and allows the branch to increase its leverage following a monetary policy easing, the increased SOE lending can also result in poor loan performance ex post, exacerbating credit misallocaiton.

V.4. **Effects of policy changes on productivity.** The misallocation effects of monetaty 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, then we should observe negative effects of monetary policy shocks on aggregate productivity. We now examine this possibility using province-level annual data.

TABLE 8. Ex post performance of SOE loans

	(1)	(2)	(3)	(4)
	Overdue	*Overdue*	*Overdue*	*Overdue*
	OLS	OLS	probit	probit
SOE	-0.0047***	0.0159***	-0.0042**	0.0327***
	(0.0017)	(0.0021)	(0.0017)	(0.0024)
Credit Rating		-0.0161***		-0.0155***
		(0.0002)		(0.0002)
Branch FE	yes	yes	yes	yes
year FE	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes
Observations	323,486	232,073	319,686	228,083
R^2	0.041	0.111		

Notes: This table reports the estimated ex post performance of SOE loans and loans with high credit ratings. *Overdue* is a dummy variable that is equal to one if the loan is overdue or rolled over by the bank at the due time; and it is equal to zero otherwise. The definitions of SOE and Credit Rating are the same as those in Table 6. Columns (1) and (2) show the estimates of OLS, while Columns (3) and (4) show the estimates from a probit model. Margins are reported for the probit models. All models include controls for the branch fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, 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.

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 risk history. The regression also controls for the year fixed effects and the province fixed effects. Table 9 shows the estimation results using OLS (Column (1)) and the dynamic-panel generalized method of moments (GMM) approach (Column (2)).

A coherent pattern emerges from these empirical specifications: 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

TABLE 9. Bank risk-taking and aggregate productivity

	(1) TFP growth OLS	(2) TFP growth 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) or AR(2) p-value		0.036, 0.746
Hansen or 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 shock 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.

shock to monetary policy in the post-2013 period reduces provincial TFP growth by about 0.26 percentage point.[32] 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.

[32] 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 $0.914 \times 0.28\% \approx 0.26\%$.

VI. Conclusion

We present robust evidence that the implementation of Basel III regulations in 2013 has significantly changed Chinese banks' risk-taking behaviors and their responses to monetary policy shocks. After the regulatory policy changes, banks reduced risk-taking by increasing the share of lending to high credit-rating firms, both on average and conditional on monetary policy expansions. The declines in bank risk-taking following a monetary policy expansion 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 22% after the new regulations were put in place in 2013.

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.

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 for 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 firms' 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 given default, exposure at default, and the correlation and maturity of each individual exposure.

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.

The difference between the effective CAR calculated based on these two different approaches is illustrated by Table A.1, which shows the CAR disclosure from the 2013 annual report of the Bank of China (BoC), one of the Big Five, and the Bank of China Group.

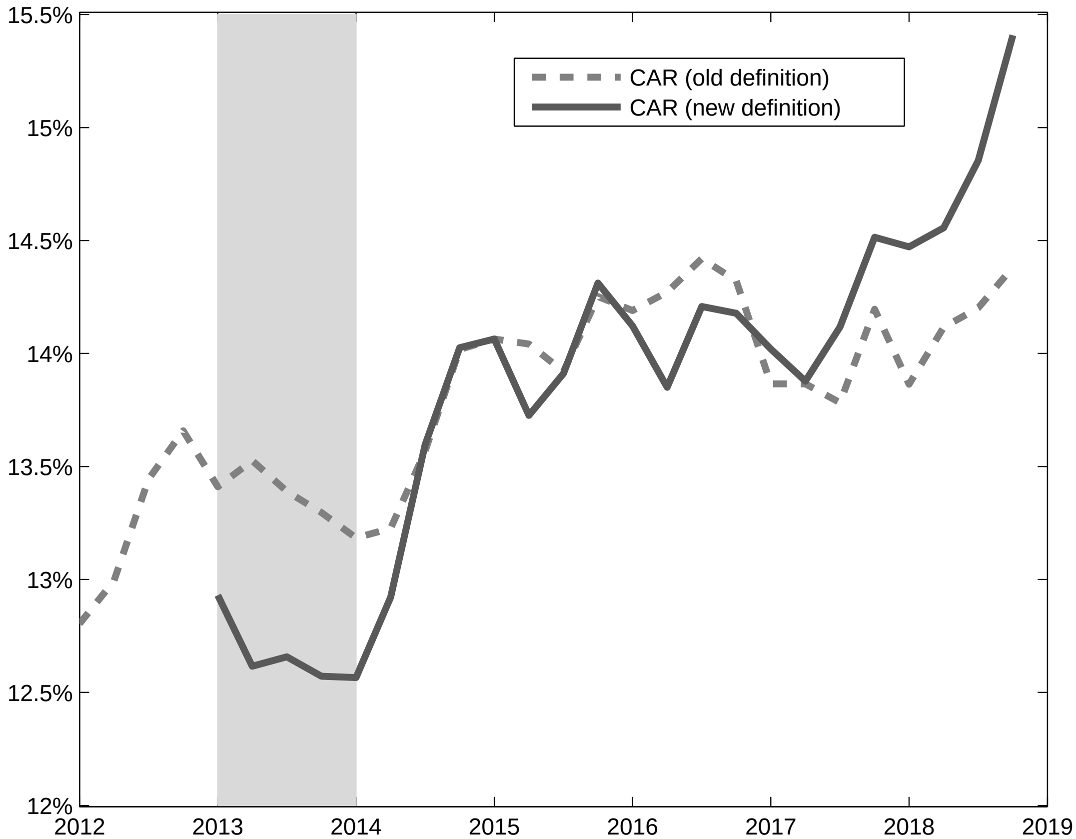
Table A.1. Capital and capital adequacy ratios

	End of 2014		End of 2013	
	BoC Group	BoC	BoC Group	BoC
CAR based on IRB approach under the new (2012) *Capital Rules*				
Core Tier 1 Capital	1,054,389	929,096	912,948	802,861
Tier 1 Capital	1,127,312	1,000,841	913,646	802,861
Capital	1,378,026	1,234,879	1,173,347	1,040,740
Core CAR (Tier 1)	10.61%	10.48%	9.69%	9.55%
CAR (Tier 1)	11.35%	11.29%	9.70%	9.55%
CAR	13.87%	13.93%	12.46%	12.38%
CAR based on RW approach under the old (2004) regulations				
Core CAR	11.04%	11.20%	10.73%	10.92%
CAR	14.38%	14.45%	13.47%	13.43%

Notes: The amounts of capital are in units of million yuans. For the CARs in the first panel, the bank uses the IRB approach to assess risk-weighted assets for 2014 and the RW approach for 2013.

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.

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 RW approach (dashed line) and the new IRB approach (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.

Appendix B. Extension with Bank Competition

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.[5] 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

[5]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.

financed by loans from individual banks indexed by i, with the constant-elasticity-of-substitution (CES) aggregation technology

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

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,

$$V = e \max_{\{\sigma,d\}} \int_{\underline{R}(\sigma)}^{\bar{R}(\sigma)} \max\left\{g(K) R\lambda - r(\lambda - 1), 0\right\} \mathrm{d}\mathbf{F}(R), \tag{B.2}$$

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

$$V = \max_{\{\sigma\}} \frac{eg(K)}{2\psi\sigma^{\rho+1}} \left[\bar{R}(\sigma) - R^*(\sigma; K)\right]^2, \tag{B.3}$$

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

$$R^*(\sigma; K) = \frac{r(1 - \psi\sigma^\rho)}{g(K)}. \tag{B.4}$$

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

$$\frac{(\rho+1)}{2\sigma}\left[\bar{R}(\sigma) - R^*(\sigma; K)\right] = \frac{\partial\left[\bar{R}(\sigma) - R^*(\sigma; K)\right]}{\partial\sigma} + \frac{\partial g(K)/\partial\sigma}{2g(K)}\left[\bar{R}(\sigma) + R^*(\sigma; K)\right]. \tag{B.5}$$

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 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

$$\frac{\partial g(K)}{\partial\sigma_i} / g(K) = \frac{(1-\alpha)\rho}{N\sigma}, \tag{B.6}$$

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 B.1.

Proposition B.1. *The optimal project risk (σ) decreases with the level of banking competition (N), that is,*

$$\frac{\partial \sigma}{\partial N} < 0. \tag{B.7}$$

Proof. See Appendix S.1. □

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 (B.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) in order 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 B.2.

Proposition B.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,

$$\frac{\partial}{\partial N}\left[\frac{\partial \sigma}{\partial r}|_{\rho=1} - \frac{\partial \sigma}{\partial r}|_{\rho=0}\right] > 0. \tag{B.8}$$

Proof. See Appendix S.1. □

Appendix C. Further robustness checks

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

Measuring monetary policy shocks based on an interest rate rule. In the baseline empirical model, we focus on a quantity-based monetary policy rule for measuring 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).[6] To check the robustness of our results to alternative measures of monetary policy shocks, we estimate a Taylor rule with a short-term nominal interest rate as the policy instrument and use the residuals to measure monetary policy shocks.

Specifically, the Taylor rule takes the form

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

where 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. In the estimation, we use 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.

We estimate the baseline empirical specification (24), with the monetary policy shock measured by the Taylor rule residuals. The results are displayed in Table C.1. Columns (1) and (2) report the results when we use Shibor as a measure of the policy interest rate, and Columns (3) and (4) report the results when we use Repo instead. In both cases, using either OLS or probit estimation, we obtain a positive and significant coefficient estimate for the double interaction term $RiskH_j \times Post_y$ and a significant and negative coefficient estimate for the triple interaction term ($RiskH_j \times MP_t^{Shibor} \times Post_y$ or $RiskH_j \times MP_t^{Repo} \times Post_y$). Thus, the implementation of Basel III reduced risk-taking of those branches with high shares of NPLs in the pre-2013 period, and the impact is larger following an expansionary monetary policy shock. These results confirm those obtained from the baseline model, suggesting that our main findings are robust to alternative 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,

[6]Chang et al. (2015) discuss the implications of interest rate rules for macroeconomic stability and welfare in a calibrated 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).

Table C.1. Effects of regulations on bank risk-taking: Interest rate shocks

	(1)	(2)	(3)	(4)
	$HighR$	$HighR$	$HighR$	$HighR$
	OLS	probit	OLS	probit
$RiskH_j \times MP_t^{Shibor} \times Post_y$	-0.5599**	-0.6290**		
	(0.2660)	(0.2934)		
$RiskH_j \times MP_t^{Shibor}$	0.6538***	0.6462***		
	(0.2361)	(0.2344)		
$RiskH_j \times MP_t^{Repo} \times Post_y$			-0.5105**	-0.5103*
			(0.2452)	(0.2718)
$RiskH_j \times MP_t^{Repo}$			0.5905***	0.5989***
			(0.2189)	(0.2182)
$RiskH_j \times Post_y$	0.0091***	0.0088***	0.0090***	0.0086***
	(0.0012)	(0.0015)	(0.0012)	(0.0015)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes
R^2	0.120		0.120	
Observations	230,371	174,147	230,371	174,147

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. Columns (1), (3) and Columns (2), (4) use OLS and probit models, respectively. 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, 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.

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 expand the set of independent variables in our baseline specification and include 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 independent variables in our regression. Here, the variable $LoanRateGap_t$ 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.2 displays the estimation results when we include controls for interest rate liberalization. In the periods when the bank's average lending rate exceeds the benchmark rate (i.e., when $LoanRateGap_t > 0$), the branches with high risk exposures in the past increase the share of high-rating lending to reduce loan risks. This effect is statistically significant at the 99% level. However, when $LoanRateGap_t > 0$, an expansionary monetary policy shock *reduces* the share of high-rating lending (indicating more risk-taking), although this latter effect is insignificant.

After controlling for the effects of interest rate liberalization, we still obtain a large and significant impact of the regulatory policy changes on bank risk-taking. In the post-2013 period, high-risk branches increased their lending to high-rating firms (relative to low-risk branches), both on average and in response to an expansionary monetary policy shock. As in the baseline estimation, these effects are statistically significant at the 99% level. Thus, the changes in risk-taking that we have identified in the baseline regression are associated with changes in capital regulations; they are not driven by other reforms such as interest rate liberalization.

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.

TABLE C.2. Effects of regulations on bank risk-taking: Controlling for the impact of interest rate liberalization

	(1)	(2)
	$HighR$	$HighR$
	OLS	probit
$RiskH_j \times MP_t \times Post_y$	0.8940***	0.8059***
	(0.2045)	(0.2465)
$RiskH_j \times Post_y$	0.0067***	0.0086***
	(0.0014)	(0.0018)
$RiskH_j \times MP_t$	-0.9681***	-0.5699
	(0.3132)	(0.4011)
$RiskH_j \times MP_t \times LoanRateGap_{t-1}$	2.4494	0.8270
	(2.7226)	(3.9182)
$RiskH_j \times LoanRateGap_{t-1}$	0.0135	-0.0021
	(0.0163)	(0.0229)
Branch FE	yes	yes
Industry FE	yes	yes
Year-quarter FE	yes	yes
Initial controls × year FE	yes	yes
R^2	0.190	
Observations	210,983	140,443

Notes: Columns (1) and (2) report the results from OLS and probit regressions , respectively. The margin effects are reported for the probit model. 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, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, 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.

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 (24), replacing the variable $Post_y$ in the baseline model with $DeLev_y$. Table C.3 shows the estimation results. Unlike the banking regulation policy changes under Basel III, the deleveraging policy had no significant impact on bank risk-taking (the coefficient of $RiskH_j \times Delev_y$ is insignificant) and even reduced the high-rating lending (the coefficient of $RiskH_j \times MP_t \times Delev_y$ is significantly negative).

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.4 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, regardless of whether we control for the effects of the capitalization level (CAR_{y-1}). This finding confirms 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.4, in the post-2013 period, high-risk branches are more likely to lend to highly rated firms, both on average and conditional on an expansionary monetary policy shock.

Additional controls. Our baseline regression includes controls for branch fixed effects, year-quarter 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.3. Effects of deleveraging policy on bank risk-taking: A placebo test

	(1)	(2)	(3)	(4)
	$HighR$	$HighR$	$HighR$	$HighR$
	OLS	OLS	probit	probit
$RiskH_j \times MP_t \times Delev_y$	-0.9762**	-1.2450***	-0.6532	-0.7924
	(0.4038)	(0.4243)	(0.7475)	(0.7774)
$RiskH_j \times Delev_y$	0.0009	-0.0030	0.0024	-0.0021
	(0.0016)	(0.0019)	(0.0029)	(0.0033)
$RiskH_j \times MP_t$	-0.3167***	-2.9723**	-0.2905***	-1.5863
	(0.0877)	(1.5141)	(0.1103)	(1.9494)
$RiskH_j \times MP_t \times CAR_{y-1}$		0.2067*		0.1068
		(0.1113)		(0.1465)
$RiskH_j \times CAR_{y-1}$		0.0025***		0.0030***
		(0.0008)		(0.0011)
Branch FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial control × year FE	yes	yes	yes	yes
R^2	0.194	0.194		
Observations	212,631	212,631	141,498	141,498

Notes: Columns (1)-(2) and (3)-(4) report the results in OLS and probit estimations, respectively. $DeLev_y = 1$ if $y \geq 2016$ and 0 otherwise. All other variables have the same definitions as those in the baseline estimations. The margin effects are reported for the probit model. The monetary policy shock is constructed using the approach in Chen et al. (2018). 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, 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.

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.[7]

[7]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.

TABLE C.4. Controlling for effects of anti-corruption campaigns

	(1)	(2)
$HighR_{i,j,t}$	OLS	OLS
$RiskH_j \times MP_t \times Post_y$	0.9095***	1.8515***
	(0.1999)	(0.3218)
$RiskH_j \times Post_y$	0.0061***	0.0035*
	(0.0013)	(0.0019)
$RiskH_j \times MP_t$	-0.7234***	7.9030***
	(0.1713)	(2.1433)
$AntiCorrup_j \times Post_y$	0.0168***	0.0168***
	(0.0014)	(0.0014)
$AntiCorrup_j \times MP_t$	0.5798***	0.5777***
	(0.1768)	(0.1768)
$AntiCorrup_j \times MP_t \times Post_y$	-0.4759**	-0.4744**
	(0.2052)	(0.2052)
$RiskH_j \times MP_t \times CAR_{y-1}$		-0.6823***
		(0.1707)
$RiskH_j \times CAR_{y-1}$		0.0015
		(0.0009)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Industry FE	yes	yes
Initial controls $\times$ year FE	yes	yes
R^2	0.195	0.195
Observations	212,631	212,631

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. Both models include controls for the branch fixed effects, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, 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. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

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.

The third additional control that we consider is the industry fixed effects.

Table C.5 shows the regression results with these additional controls (one at a time), for both the OLS (the first three columns) and the probit (the last three columns) estimation approaches. Our main findings in the baseline estimation remain robust: the regulatory changes raised the relative share of SOE lending by high-risk branches in response to a positive monetary policy shock.

Clustering standard errors at bank branch and year-quarter levels. In the text, we have reported regression results with robust standard errors. Here, we show that the results are robust when the standard errors are clustered at the bank branch and year-quarter levels. The regression results are shown in Table C.6 below.

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 now 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 of 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.7.

Using a sample with multiple banks. The advantage of using our baseline sample is that we have detailed loan-level data. The disadvantage is that the data are from a single bank. One concern 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 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.

Table C.5. Additional controls

	(1)	(2)	(3)	(4)
$HighR_{i,j,t}$	OLS	OLS	OLS	OLS
$RiskH_j \times MP_t \times Post_y$	0.9026***	0.9066***	1.8431***	1.8459***
	(0.1995)	(0.1996)	(0.3216)	(0.3222)
$RiskH_j \times Post_y$	0.0062***	0.0061***	0.0038**	0.0038**
	(0.0013)	(0.0013)	(0.0019)	(0.0019)
$RiskH_j \times MP_t$	-0.7157***	-0.7251***	7.9610***	7.9043***
	(0.1708)	(0.1707)	(2.1437)	(2.1474)
$RiskH_j \times CAR_{y-1}$			-0.6862***	-0.6826***
			(0.1707)	(0.1710)
$RiskH_j \times MP_t \times CAR_{y-1}$			0.0015	0.0013
			(0.0009)	(0.0009)
$InitProfit_j$ × year FE	yes	yes	yes	yes
$InitSOE_j$ × year FE	no	yes	no	yes
Industry FE	yes	yes	yes	yes
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes
R^2	0.194	0.194	0.194	0.195
Observations	212,631	212,631	212,631	212,631

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, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, 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.6. Clustered standard errors

$HighR_{i,j,t}$	(1) OLS	(2) OLS
$RiskH_j \times MP_t \times Post_y$	1.8431***	1.8431***
	(0.4056)	(0.2599)
$RiskH_j \times Post_y$	0.0038	0.0038
	(0.0041)	(0.0039)
$RiskH_j \times MP_t$	7.9610***	7.9610***
	(1.7375)	(0.7539)
$RiskH_j \times CAR_{y-1} \times MP_t$	-0.6862***	-0.6862***
	(0.1327)	(0.0578)
$RiskH_j \times CAR_{y-1}$	0.0015	0.0015
	(0.0015)	(0.0010)
Double-Clustered at	Branch & Year-quarter	Firm & Year-quarter
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls × year FE	yes	yes
R^2	0.194	0.194
Observations	212,631	212,631

Notes: The numbers in parentheses show the robust standard errors double clustered at branch (firm) and year-quarter levels. 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.

To further examine the robustness of our results, we use confidential data from 17 Chinese banks for the period from 2007:Q1 to 2013:Q2 to examine how changes in the CAR regulations in the beginning of 2013 may have changed bank risk-taking.[8]

Since the multiple-bank sample does not have credit rating information, we use the share of the number of SOE loans in the total number of corporate loans ($SOE_{b,t}$) as the dependent variable. We measure the risk history of a bank by two alternative indicators. One is a dummy variable that equals one if a bank's average NPL ratio before 2013 (i.e., 2007-2012) is above the median; the other is a dummy variable that equals one if a

[8]Unfortunately, we do not have loan-level data from these banks and the sample ends by 2013:Q2. Thus, the sample size here is much smaller than that in the baseline regressions.

TABLE C.7. Alternative measure of risk history

$HighR_{i,j,t}$	(1) OLS	(2) OLS
$RiskH2_j \times MP_t \times Post_y$	0.2581***	0.2613***
	(0.0806)	(0.0806)
$RiskH2_j \times Post_y$	0.0030***	0.0028***
	(0.0006)	(0.0006)
$RiskH2_j \times MP_t$	-0.2660***	-0.2559***
	(0.0676)	(0.0675)
$RiskH2_j \times MP_t \times CAR_{y-1}$		-0.0107
		(0.0069)
$RiskH2_j \times CAR_{y-1}$		0.0020***
		(0.0007)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Industry FE	yes	yes
Initial controls × year FE	yes	yes
Observations	212,631	212,631
R^2	0.194	0.194

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, the year-quarter fixed effects, and the average firm characteristics (including size, age, leverage, 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.

bank's average loan delinquency ratio ($Delinq$) before 2013 is above the median. We use the same measures for monetary policy shocks (MP_t) and the post-Basel III indicator ($Post_y$) as in the baseline specification.

Table C.8 displays the regression results. Column (1) shows that high-risk banks (measured by the past NPL) respond to monetary policy easing by raising the share of SOE lending after the implementation of the Basel III regulations, confirming the previous findings. However, absent monetary policy shocks, the average effect of the regulation changes on high-risk banks' SOE lending is no longer significant. We obtain

TABLE C.8. Regressions using the sample with multiple banks

	(1)	(2)	(3)	(4)
$SOE_{b,t}$	$RiskH$ = NPL	$RiskH$ = Delinq	$RiskH$ = NPL	$RiskH$ = Delinq
$RiskH_b \times MP_t \times Post_y$	0.6515***	2.605***	0.7970***	3.1895***
	(0.1270)	(0.1649)	(0.1243)	(0.1955)
$RiskH_b \times MP_t$	0.0727	0.6071	0.0727	0.6071
	(0.8159)	(0.7771)	(0.8176)	(0.7802)
$RiskH_b \times Post_y$	-0.0021	-0.0122	-0.0014	-0.0134
	(0.0121)	(0.0123)	(0.0125)	(0.0125)
$RiskH_b \times MP_t \times CAR_{b,t}$			-0.5817**	-2.3379***
			(0.2449)	(0.7753)
$RiskH_b \times CAR_{b,t}$			-0.0030	0.0049
			(0.0066)	(0.0061)
Observations	442	442	442	442
R-squared	0.246	0.249	0.246	0.250
Other Controls	-	-	yes	yes
Bank FE	yes	yes	yes	yes
Year-Quater FE	yes	yes	yes	yes

Notes: The columns report OLS estimation results using the sample with 17 Chinese banks over the periods from 2007:Q1 to 2013:Q2. The dependent variable ($SOE_{b,t}$) for each regression is the share of the number of SOE loans in the total number of corporate loans for bank b in quarter t. The set of independent variables includes a bank's risk history ($RiskH_b$), which is a dummy variable that equals one if the bank's average non-performing loan ratio (NPL) in 2007-2012 is above the median (Columns (1) and (3)) or the average loan delinquency ratio (Delinq) in 2007-2012 is above the median (Columns (2) and (4)); a measure of monetary policy shocks (MP_t) constructed using the approach in Chen et al. (2018); and the post-Basel III dummy ($Post_y$). In Columns (3) and (4), the regressions include the interactions of an indicator for the level of capitalization $CAR_{b,t}$ with the risk history and the monetary policy shock, where $CAR_{b,t}$ is a dummy variable that equals one if and only if the bank b is systemically important and the quarter t is after the implementation of the Basel III regulations in the beginning of 2013. All regressions include controls for bank fixed effects and the year-quarter fixed effects. The regressions in Columns (3) and (4) also include controls for the level of $CAR_{b,t}$ and its interactions with MP_t and with $RiskH_b$. The numbers in the parentheses indicate robust standard errors double clustered at bank and year-quarter level. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

similar results when we measure the risk history using the loan delinquency ratio (Column (2)).

Columns (3) and (4) add controls for the effects from the level of capitalization. In particular, we construct a dummy variable $CAR_{b,t}$ that equals one if and only if bank b is systemically important and the quarter t is after the implementation of the Basel III regulations in the beginning of 2013. This dummy variable captures the differential impact of the regulations on the required capitalization levels for systemically important banks, because the new regulations raised the minimum CAR for systemically important banks from 8% to 11.5% (compared to 10.5% for other banks). As shown in the table, banks with higher capitalization under the new regulations responded to an expansionary monetary policy shock by *reducing* the share of SOE loans, implying increased risk-taking (the coefficient on the triple interaction term $RiskH_b \times MP_t \times CAR_{b,t}$ is significantly negative). After controlling for the heterogeneous changes in the required CAR across banks, the new regulations still significantly reduce bank risk-taking conditional on monetary policy easing (the coefficient on the triple interaction term $RiskH_b \times MP_t \times Post_y$ is significantly positive).

These results from the multiple-bank sample confirm our baseline finding: under the new capital regulations, high-risk banks respond to a monetary policy easing by reducing risk-taking; and the reduction in risk-taking works mainly through the risk-weighting channel.

Appendix D. More results of effects on resource misallocation

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 dispersions of marginal product of factors. We 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 MPK dispersion within each province using the data of publicly listed firms. Table D.2 reports the 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)

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).

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

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, 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.

References

Adrian, Tobias and Hyun Song Shin, "Financial intermediaries and monetary economics," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3, Elsevier, 2010, chapter 12, pp. 601–650.

Barrot, Jean-Noel, "Trade credit and industry dynamics: Evidence from trucking firms," *Journal of Finance*, 2016, *71* (5), 1975–2016.

Bernanke, Ben S., "The New Tools of Monetary Policy," January 2020. American Economic Association Presidential Address.

Bertrand, Marianne and Sendhil Mullainathan, "Are CEOs rewarded for luck? The ones without principals are," *The Quarterly Journal of Economics*, 2001, *116* (3), 901–932.

Bleck, Alexander and Xuewen Liu, "Credit Expansion and Credit Misallocation," *Journal of Monetary Economics*, 2018, *94*, 27–40.

Bonfim, Diana and Carla Soares, "The Risk-Taking Channel of Monetary Policy: Exploring All Avenues," *Journal of Money, Credit and Banking*, 2018, *50* (7), 1507–1541.

Borio, Claudio and Haibin Zhu, "Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism?," *Journal of Financial Stability*, 2012, *8*, 236–251.

Boyd, John H. and Gianni De Nicoló, "The Theory of Bank Risk Taking and Competition Revisited," *The Journal of Finance*, 2005, *60* (3), 1329–1343.

Brandt, Loren, Trevor Tombe, and Xiaodong Zhu, "Factor market distortions across time, space and sectors in China," *Review of Economic Dynamics*, 2013, *16* (1), 39–58.

Bruno, Valentina and Hyun Song Shin, "Capital flows and the risk-taking channel of monetary policy," *Journal of Monetary Economics*, 2015, *71*, 119–132.

Caglio, Cecilia R, R. Matthew Darst, and Sebnem Kalemli-Ozcan, "Risk-Taking and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms," Working Paper 28685, National Bureau of Economic Research April 2021.

Chang, Chun, Kaiji Chen, Daniel F. Waggoner, and Tao Zha, "Trends and Cycles in China's Macroeconomy," in Martin Eichenbaum and Jonathan A. Parker, eds., *NBER Macroeconomics Annual 2015*, Vol. 30, Chicago: University of Chicago Press, 2016, pp. 1–84.

———, Zheng Liu, and Mark M Spiegel, "Capital controls and optimal Chinese monetary policy," *Journal of Monetary Economics*, 2015, *74*, 1–15.

———, ———, Mark M. Spiegel, and Jingyi Zhang, "Reserve Requirements and

Optimal Chinese Stabilization Policy," *Journal of Monetary Economics*, May 2019, *103*, 33–51.

Chen, Kaiji, Jue Ren, and Tao Zha, "The nexus of monetary policy and shadow banking in China," *American Economic Review*, 2018, *108* (12), 3891–3936.

Chen, Zhuo, Zhiguo He, and Chun Liu, "The Financing of Local Government in China: Stimulus Loan Wanes and Shadow Banking Waxes," *Journal of Financial Economics*, 2020, *137*, 42–71.

Coimbra, Nuno and Hélène Rey, "Financial Cycles with Heterogeneous Intermediaries," *The Review of Economic Studies*, 04 2023.

Cong, Lin William, Haoyu Gao, Jacopo Ponticelli, and Xiaoguang Yang, "Credit Allocation Under Economic Stimulus: Evidence from China," *Review of Financial Studies*, 2019, *32* (9), 3412–3460.

Degryse, Hans and Steven Ongena, "Distance, Lending Relationships, and Competition," *The Journal of Finance*, 2005, *60* (1), 231–266.

Delis, Manthos D, Iftekhar Hasan, and Nikolaos Mylonidis, "The risk-taking channel of monetary policy in the US: Evidence from corporate loan data," *Journal of Money, Credit and Banking*, 2017, *49* (1), 187–213.

Dell'Ariccia, Giovanni, Luc Laeven, and Gustavo A Suarez, "Bank leverage and monetary policy's risk-taking channel: evidence from the United States," *Journal of Finance*, 2017, *72* (2), 613–654.

———, ———, and Robert Marquez, "Monetary policy, leverage, and bank risk-taking," *Journal of Economic Theory*, 2014, *149*, 65–99.

Fernald, John G., Mark M. Spiegel, and Eric T. Swanson, "Monetary policy effectiveness in China: Evidence from a FAVAR model," *Journal of International Money and Finance*, 2014, *49*, 83–103. The Pacific Rim Economies and the Evolution of the International Monetary Architecture.

Gao, Haoyu, Hong Ru, Robert M. Townsend, and Xiaoguang Yang, "Rise of Bank Competition: Evidence from Banking Deregulation in China," May 2019. NBER Working Paper No. 25795.

Gertler, Mark and Nobuhiro Kiyotaki, "Financial intermediation and credit policy in business cycle analysis," in "Handbook of monetary economics," Vol. 3, Elsevier, 2010, pp. 547–599.

Girardin, Eric, Sandrine Lunven, and Guonan Ma, "China's evolving monetary policy rule: from inflation-accommodating to anti-inflation policy," Technical Report 641, BIS Working Papers May 2017.

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez, "Capital allocation and productivity in South Europe," *The Quarterly Journal of Economics*, 2017, *132* (4), 1915–1967.

Hachem, Kinda and Zheng Song, "Liquidity Rules and Credit Booms," *Journal of Political Economy*, 2021, *129* (10), 2721–2765.

Hsieh, Chang-Tai and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *The Quarterly Journal of Economics*, November 2009, *124* (4), 1403–1448.

______ **and Zheng (Michael) Song**, "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China," in Janice C. Eberly and James H. Stock, eds., *Brookings Papers on Economic Activity*, Vol. Spring The Brookings Institution March 2015, pp. 295–366.

HUANG, YI, MARCO PAGANO, and UGO PANIZZA, "Local Crowding-Out in China," *The Journal of Finance*, 2020, *75* (6), 2855–2898.

Jiménez, Gabriel, Jose A. Lopez, and Jesús Saurina, "How Does Competition Affect Bank Risk-taking?," *Journal of Financial Stability*, 2013, *9* (2), 185–195.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, "Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?," *Econometrica*, 2014, *82* (2), 463–505.

Keeley, Michael C., "Deposit Insurance, Risk, and Market Power in Banking," *American Economic Review*, 1990, *80* (5), 1183–1200.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, September 2008, *98* (4), 1413–42.

Liu, Zheng, Mark M. Spiegel, and Jingyi Zhang, "Optimal capital account liberalization in China," *Journal of Monetary Economics*, January 2021, (117), 1041–1061.

______**, Pengfei Wang, and Zhiwei Xu**, "Interest rate liberalization and capital misallocations," *American Economic Journal: Macroeconomics*, 2021, *13* (2), 373–419.

Maddaloni, Angela and José-Luis Peydró, "Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the Euro-area and the US lending standards," *The Review of Financial Studies*, 2011, *24* (6), 2121–2165.

Martinez-Miera, David and Rafael Repullo, "Does Competition Reduce the Risk of Bank Failure?," *The Review of Financial Studies*, 08 2010, *23* (10), 3638–3664.

Reis, Ricardo, "The Portugese Slump and Crash and the Euro Crisis," *Brookings Papers on Economic Activity*, 2013, *44* (1), 143–210.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, "Growing Like China," *The American Economic Review*, 2011, *101* (1), 196–233.

Stein, Jeremy C., "Overheating in Credit Markets: Origins, Measurement, and Policy Responses," February 2013. Speech presented at "Restoring Household Financial Stability after the Great Recession: Why Household Balance Sheets Matter," A Research Symposium sponsored by the Federal Reserve Bank of St. Louis.

Stiglitz, Joseph E. and Andrew Weiss, "Credit Rationing in Markets with Imperfect Information," *American Economic Review*, 1981, *71* (3), 393–410.