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

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

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-difference identification, exploiting cross-sectional differences in lending behaviors between high-risk and low-risk bank branches before and after the new regulations. We find that, through a risk-weighting channel, changes in regulations significantly reduced bank risk-taking, both on average and conditional on monetary policy easing. However, banks reduce risk-taking by increasing lending to ostensibly low-risk state-owned enterprises (SOEs) under government guarantees, despite their low average productivity.

I. INTRODUCTION

In response to the 2008-09 Global Financial Crisis and the recent COVID-19 pandemic, central banks have aggressively eased monetary policy to mitigate recessions. Such policy interventions, however, have raised concerns about financial stability. If the policy interest rate remains persistently low, it might 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 monetary policy tightening that raises the returns

on safe assets should induce banks to increase holdings of safe securities and thus reducing risk-taking. In contrast, the risk-shifting models have the opposite predictions. In those models, asymmetric information between banks and borrowers and limited liabilities of banks 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, making 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 liabilities, a more leveraged bank has a greater incentive for risk-taking when it faces an increase in funding costs. Thus, changes in banking regulations that affect bank leverage can also affect risk-taking and its responses to monetary policy shocks.

In this paper, we examine the empirical link between monetary policy and bank risk-taking using Chinese data, exploiting cross-sectional differences in banks' responses to regulation changes for 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 (IRB) approach 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 reducing loan risks.

To study how the regulatory policy changes can affect bank risk-taking and its responses to monetary policy shocks, we build a theoretical model in which banks optimize loan portfolios subject to a CAR constraint. In the model, the effective risk of a loan portfolio is the product of an aggregate risk that is common to all banks and an idiosyncratic risk that is bank-specific. The bank-specific risks may reflect the location of a bank (or a branch) or the industries (or firms) to which the bank concentrates its lending (Zentefis, 2020).

The model predicts that, in response to a regulation that raises the sensitivity of risk-weighted assets to loan risks (i.e., risk-weighting sensitivity), all banks choose to

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

reduce risk-taking; and those 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 sensitivity to risk weighting 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 empirical identification, and our empirical findings are consistent with the model's predictions.

For our empirical investigation, 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 sheet, profits, and cash flows). We merge the two data sources by matching firm names. We use the merged data, with about 400,000 unique firm-loan pairs for the periods from 2008 to 2017, to estimate the empirical relation between bank risk-taking and monetary policy shocks, both before and after the implementation of Basel III. 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).

In light of the theoretical predictions of the model, we identify the effects of the Basel III regulations on bank risk-taking—both on average and conditional on monetary policy shocks—by exploiting the cross-sectional differences in branch-specific risks. In practice, we measure branch-specific risks by the share of non-performing loans (NPL) before the Basel III regulations were put in place. Our theory implies that a bank branch with a higher level of idiosyncratic risks would take on more risks and should thus have a greater share of NPL on average.

In our empirical specification, we measure the level of loan risks by a dummy variable that equals one if the loan is extended to an SOE firm (SOE). Under prevailing government policies, SOE firms are perceived as ex ante low-risk borrowers.[2] The main

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[2]As we show in Section IV.1.2, all else being equal, SOE loans receive higher credit ratings than loans to private firms, reflecting government guarantees on SOE loans. In this sense, SOE loans are considered ex ante low-risk lending.

independent variables of interest include (1) an interaction term between a dummy variable indicating the post-2013 periods after the new regulations were implemented ($Post$) and an indicator of whether a branch has had high NPL shares before 2013 ($RiskH$); and (2) a triple interaction term between $Post$, $RiskH$, and our measure of monetary policy shocks (MP). We control for the year-quarter fixed effects, branch fixed effects, and firm-year fixed effects. According to our theory, a bank with a higher NPL share in the past (i.e., high-risk branches) should be more likely to reduce risk-taking under the new regulations, both on average and conditional on monetary policy easing. Thus, we should expect the coefficients on both interaction terms to be positive.

Consistent with the theory, we find that, after the Basel III regulations were implemented in 2013, high-risk branches indeed reduced risk-taking relative to low-risk branches by increasing the share of lending to SOE firms; and the decline in risk-taking is observed both on average and conditional on monetary policy expansions. The estimated declines in bank risk-taking are statistically significant and economically important. Our baseline estimation suggests that a one standard deviation increase in the M2 growth shock raises the probability of SOE lending by 6.3% under the new regulations.

We further find that the decline in bank risk-taking induced by the new capital regulations was driven primarily by changes in the sensitivity to risk weighting, not by changes in capitalization. When we control for the level of capitalization in our regressions, we estimate that the same monetary policy shock raises the probability of SOE lending by up to 14%, more than twice that from the baseline estimation (6.3%).[3] Under the new regulations, a bank branch can raise its capital adequacy ratio by reducing the level of risk-weighted assets; and since the IRB approach increased the sensitivity of risk weighting to credit risks, an effective way to reduce the level of risk-weighted assets is to increase the share of loans to *de jure* low-risk borrowers such as SOEs.[4]

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[3]In the expanded regression that includes controls for capitalization, we find that a higher level of capitalization (measured by the effective CAR) is associated with a *decline* in the share of lending to SOEs following an expansionary monetary policy shock, implying *more* risk-taking. This finding is in line with that of Dell'Ariccia et al. (2017), who use U.S. loan-level data; but it is different from that of Jiménez et al. (2014), who use Spanish data.

[4]In practice, the capital requirements apply at the consolidated bank level. The value of bank capital (i.e., the numerator of the CAR) is also determined at the bank level. To meet the CAR requirements, the bank headquarter sets guidelines on risk-weighted assets for provincial branches, which are then trickled down to lower level branches. Under this institutional arrangement, branches do not have control over bank capital. To increase leverage, they would have to reduce the risk weights on their loans.

Our evidence also suggests that the observed changes in bank risk-taking behaviors after 2013 reflect primarily changes in loan supply decisions instead of changes in loan demand conditions. To isolate the loan supply channel, we focus on the subsample of firms that borrow from multiple bank branches, which allows us to control for time-varying demand factors.[5] We find that an expansionary monetary policy shock in the post-2013 period leads to a significant reduction in the loan interest rate offered to SOE firms by high-risk branches but a significant increase in the loan rate for non-SOEs. That is, controlling for borrower characteristics, lenders favored SOE borrowers under the new regulations. This confirms our baseline finding that the changes in regulations have reduced bank risk-taking following monetary policy easing, and the reduction in risk-taking reflects changes in lender behaviors rather than those in demand factors.

The risk-weighting mechanism that is present at the micro-level has important implications for the transmission of monetary policy to the macroeconomy. Raising the risk-weighting sensitivity reduces bank risk-taking following an expansionary monetary policy. However, banks reduce risk-taking by increasing the share of lending to SOEs. Since SOEs have lower productivity on average than private firms (Hsieh and Klenow, 2009), an increase in the share of lending to SOEs would reduce aggregate productivity. Furthermore, since SOEs in China enjoy preferential credit access under government guarantees of their loans, they have lower marginal product of capital than private firms (Song et al., 2011; Chang et al., 2016). Increased lending to SOEs can exacerbate the over-investment problem, further reducing allocative efficiency (Liu et al., 2020). In line with these logics, we document evidence that, at the province level, a positive monetary policy shock significantly reduces TFP growth rates after the new regulations were implemented, but not before. Although SOE loans receive *de jure* high credit ratings and are considered *ex ante* low-risk loans under government guarantees, our evidence indicates that the *ex post* performance of SOE loans—measured by the share of non-performing or overdue loans—is significantly worse than average. This evidence is consistent with the misallocation channel.

II. Related literature

Our work contributes 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

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[5]This identification approach is similar to that used by Jiménez et al. (2014).

has documented some evidence of the risk-taking channel. Examples include Maddaloni and Peydró (2011), Bruno and Shin (2015), Delis et al. (2017), and Bonfim and Soares (2018). In a complementary study, Chen et al. (2020) use loan-level data from a large Chinese bank to study the aggregate and distributional effects of changes in China's mortgage lending policy in 2014-2016. Unlike our study that focuses on bank lending to firms, they focus on mortgage lending to households.

On the theory side, our model with bank portfolio choices is closely related to the model of bank liquidity management by Bianchi and Bigio (2017). In their model, banks face liquidity risks on the liability side (e.g., unexpected deposit withdrawals) and they have a precautionary motive of holding liquid assets such as reserves and government securities. Under binding capital requirements, a monetary policy shock leads to a tradeoff for banks between profiting from more lending and incurring greater liquidity risks on the liability side. They highlight the importance of interbank market frictions for monetary policy transmission. In our model, if one interprets the low-risk, low-return lending to SOEs as a rough counterpart to the liquid assets in their model, then banks under CAR constraints also face a tradeoff between profitable lending and increasing default risks on the asset side. That said, our focus differs from theirs. We study the implications of banking regulations (in particular, risk-weighting of assets under CAR constraints) for bank risk-taking using loan-level and firm-level data. We use the simple portfolio-choice model as a theoretical guidance for our empirical specifications.

Our paper is closely related to the empirical literature that highlights the role of bank capitalization for the risk-taking channel of monetary policy. 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. Under the Basel III regime, a bank with any given capitalization can boost its effective CAR by shifting lending to low-risk borrowers. Our baseline estimation suggests that the implementation of Basel III regulations has significantly reduced bank risk-taking in China, both on average and conditional on an expansionary monetary policy shock. This result, however, 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 twice as large.

The risk-weighting channel has important implications for capital allocations and productivity in the macroeconomy. Since SOEs are less productive than private firms, increased lending to SOEs reduces aggregate productivity. Our province-level evidence suggests that this reallocation effect of monetary policy is quantitatively important. Thus, our paper also contributes to the literature that studies the reallocation channel in the presence of credit market distortions.

Our findings lends support to the view that policy distortions favoring inefficient SOEs might lower economic growth in the long run and thus raise financial risks (Song and Xiong, 2018). By providing explicit or implicit guarantees for SOE loans, the government policy helps mitigate short-term risks in the banking sector. However, such heavy-handed interventions may divert investor attentions away from fundamentals and toward policy interventions, reducing the information efficiency of asset prices (Brunnermeier et al., 2020). Geng and Pan (2019) provide some evidence that, since the government-led credit tightening in mid-2018, perceived government supports for SOE borrowing have widened the credit spread between SOEs and non-SOEs and exacerbated the inefficiencies in credit allocations in China. Several empirical studies have also shown that the credit policy that favors SOEs in China has contributed to capital misallocations. For example, Gao et al. (2019) examine the effects of the 2009 bank entry deregulation in China using loan-level and firm-level data. They document evidence that, following the deregulation, most loans originated from new entrant banks went to SOEs, which had explicit or implicit government guarantees and are thus considered "safe" borrowers. Cong et al. (2019) examine loan-level data and find that the credit expansion during China's large-scale fiscal stimulus period in 2009-2010 disproportionally favored SOEs despite their lower average product of capital.[6] We contribute to the literature on the reallocation effects of macroeconomic policies by documenting micro evidence of the risk-taking channel.

III. A simple 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.

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[6]A partial list of the recent studies that highlights the reallocation 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), Liu et al. (2021), Chen et al. (2020), Huang et al. (2020), and Liu et al. (2020).

The economy has a competitive banking sector, with a continuum, risk-neutral banks. Each bank has an endowment of net worth $e > 0$ units of consumption goods. A bank takes deposits d from households at the risk-free interest rate r. The bank can lend (i.e., invest) up to $k = e + d$ units of goods in a risky project. The project return R is a random variable drawn from a uniform distribution with the cumulative density function (CDF) $\mathbf{F}(R)$.

For simplicity, we parameterize the distribution of R such that the mean and the variance are respectively given by

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

where $\phi_1, \phi_2 > 0$ are parameters. The effective project risk consists of two components: an aggregate risk $\sigma > 1$ that is common to all banks and an idiosyncratic risk $\Delta \geq 1$ that is specific to a bank. The idiosyncratic bank-specific risk reflects cross-sectional differences in project risks stemming from geographical locations of the banks or the customers (industries or firms) to whom a bank concentrates its lending (Zentefis, 2020).

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

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

The cumulative density function is then given by

$$\mathbf{F}(R) = \frac{R - \underline{R}\left(\sigma, \Delta\right)}{\bar{R}\left(\sigma, \Delta\right) - \underline{R}\left(\sigma, \Delta\right)} = \frac{R - \underline{R}\left(\sigma, \Delta\right)}{\sigma\Delta}. \tag{3}$$

Under our assumptions of the distribution function, the project risk depends on both σ and Δ, whereas the expected return depends only on σ, but not on Δ. In this sense, an increase in Δ represents a mean-preserving spread of the project returns.

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 socially inefficient. We focus on an equilibrium with the risk-return tradeoff.

Each bank has limited liabilities, such that it would exit the market if the realized profit falls below zero. Under deposit insurance, the households receive risk-free returns on their deposits at the interest rate r. A bank of type Δ takes as given the risk-free interest rate r and the stochastic project return $R(\sigma, \Delta)$, and chooses σ and d to solve

the profit maximizing problem

$$V = \max_{\{\sigma, d\}} \int_{\underline{R}(\sigma, \Delta)}^{\bar{R}(\sigma, \Delta)} \max \{Rk - rd, 0\} \, d\mathbf{F}(R), \tag{4}$$

subject to the flow-of-funds constraint

$$k = e + d, \tag{5}$$

and the capital adequacy ratio (CAR) constraint

$$\frac{e}{\xi(\sigma\Delta) k} \geq \tilde{\psi}. \tag{6}$$

Under the CAR constraint (6), the bank is required to maintain a CAR above the minimum level of $\tilde{\psi}$. Consistent with the Basel III regulations, the bank's CAR is measured by the ratio of bank capital e to the risk-weighted assets $\xi(\sigma\Delta)k$, where $\xi(\sigma\Delta)$ denotes the risk weighting function.[7]

The CAR constraint (6) is equivalent to a leverage constraint. Denote by $\lambda = \frac{k}{e}$ the leverage. Then the CAR constraint can be rewritten as

$$\lambda \leq \frac{1}{\tilde{\psi}\xi(\sigma\Delta)}. \tag{7}$$

Thus, tightening the CAR constraint (i.e., raising $\tilde{\psi}$) reduces the bank's borrowing capacity.

We parameterize the risk-weighting function such that $\xi(\sigma\Delta) = \mu(\sigma\Delta)^\rho$, where $\mu > 0$ and $\rho \in (0, 1)$.[8]

Under limited liability, there exists a break-even level of project return $R^*(\sigma, \Delta)$ such that the bank remains solvent if and only if the realized return $R \geq R^*(\sigma, \Delta)$. It is straightforward to show that the break-even level of project return is given by

$$R^*(\sigma, \Delta) = r\left[1 - \psi(\sigma\Delta)^\rho\right], \tag{8}$$

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[7]The risk weight $\xi(\sigma\Delta)$ is a function of the effective project risk, which depends on both σ and Δ. 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 Internal Ratings Based (IRB) approach under Basel III.

[8]To differentiate the capitalization effect and risk-weighting effect of CAR regulations, we introduce two parameters, $\tilde{\psi}$ and ρ. The parameter $\tilde{\psi}$ captures the regulations on the level of capitalization. The parameter ρ measures the risk-weighting sensitivity and captures the regulations on risk-weighting. Under our parameterization, the nonlinearity of the risk-weighting function implies a greater penalty to riskier loans in the bank's portfolio, such that each asset is assigned a unique risk weight, capturing—in reduced-form—the essence of the IRB approach in Basel III.

where $\psi \equiv \tilde{\psi}\mu$. Under the assumption that $r\psi < \frac{1}{2}$, a sufficient condition to ensure $R^*(\sigma, \Delta) > \underline{R}(\sigma, \Delta)$ is given by

$$\psi \bar{\sigma}^\rho < 1 - \frac{\left(\phi_1 - \frac{1}{2}\right)^2}{4\phi_2 r}. \tag{9}$$

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

Assuming that the CAR constraint (6) is binding, we can rewrite the bank's objective function in Eq. (4) as

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\begin{aligned}
V &= \max_{\{\sigma\}} \frac{e}{\psi(\sigma\Delta)^\rho} \int_{R^*(\sigma,\Delta)}^{\bar{R}(\sigma,\Delta)} [R - R^*(\sigma, \Delta)]\, d\mathbf{F}(R) \\
&= \max_{\{\sigma\}} \frac{e}{2\psi(\sigma\Delta)^{\rho+1}} \left[\bar{R}(\sigma, \Delta) - R^*(\sigma, \Delta)\right]^2, \tag{10}
\end{aligned}
$$

where we have used the flow-of-funds constraint (5) and the binding CAR constraint to substitute out k and d and we have also imposed the relation $d\mathbf{F}(R) = \frac{1}{\sigma\Delta}dR$. Thus, the bank profit increases with both the leverage ratio ($\lambda = \frac{1}{\psi(\sigma\Delta)^\rho}$) and the interest income ($\bar{R}(\sigma, \Delta) - R^*(\sigma, \Delta)$).

We focus an interior solution to the bank portfolio choice problem and project risk parameter such that $\sigma \in (0, \bar{\sigma})$.

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

$$\frac{1+\rho}{2\sigma}\left[\bar{R}(\sigma, \Delta) - R^*(\sigma, \Delta)\right] = \frac{\partial\left[\bar{R}(\sigma, \Delta) - R^*(\sigma, \Delta)\right]}{\partial\sigma}. \tag{11}$$

The right-hand side of the equation measures the marginal benefit of increasing the risk σ through increasing the interest income, which increases bank profits. Holding the leverage ratio constant, a higher risk raises the upper-tail of the return and reduces the break-even point $R^*(\sigma, \Delta)$. That is, $\frac{\partial\left[\bar{R}(\sigma,\Delta) - R^*(\sigma,\Delta)\right]}{\partial\sigma} > 0$. The left-hand side of the equation is the marginal cost of increasing the risk through reducing the leverage ratio, which reduces bank profits. The optimal risk-taking equates the marginal benefit to the marginal cost.

We first show that, for any given idiosyncratic risk Δ, raising the required level of capitalization (ψ) or increasing the sensitivity of risk-weighting (ρ) would reduce bank risk-taking. Furthermore, the optimal level of risk σ increases with the bank-specific risk Δ. These results are formally stated in Proposition 1 below.

Proposition 1. Under the condition (9), there exists a unique $\sigma \in (0, \bar{\sigma})$ that maximizes the bank's expected profit. The optimal σ satisfies

$$\frac{\partial\sigma}{\partial\psi} < 0, \quad \frac{\partial\sigma}{\partial\rho} < 0. \tag{12}$$

Furthermore, we have

$$\frac{\partial \sigma}{\partial \Delta} > 0. \tag{13}$$

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

Proof. See Supplemental Appendix A. $\square$

Given the CAR constraint, an expansionary monetary policy (i.e., a decline in r) induces the bank to increase its leverage but reduce risk exposures σ. A decline in r lowers the break-even rate of return $R^*(\sigma, \Delta) = r\left[1 - \psi\left(\sigma\Delta\right)^\rho\right]$ and boosts the interest income for any given leverage. Thus, the bank chooses to increase leverage. However, under the binding CAR constraint, increasing leverage requires reducing the risk. This result is formally stated in the Proposition 2.[9]

Proposition 2. The optimal leverage ratio $\lambda = \frac{k}{e}$ decreases with the risk-free interest rate, whereas the optimal level of risk σ increases with the interest rate. That is,

$$\frac{\partial \lambda}{\partial r} < 0, \quad \frac{\partial \sigma}{\partial r} > 0. \tag{14}$$

Proof. See Supplemental Appendix A. $\square$

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, with the minimum CAR increased to 10.5% from 8%. This can be interpreted as an increase in the parameter ψ in our model. The new regulations also allowed banks to adopt the Internal Ratings Based (IRB) approach to calculating risk-weighted assets for assessing a bank's CAR, increasing the sensitivity of risk-weighting to credit risks. This aspect of the regulatory policy change can be captured by an increase in the elasticity parameter ρ in our model.

As shown in Proposition 2, monetary policy easing raises bank leverage but reduces risk-taking under given capital regulations (parameterized by ψ and ρ). The results hold for all banks regardless of their idiosyncratic risks Δ.

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[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 deposit interest rate falls such that the 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 strength the relation between risk-taking and monetary policy that we establish in Proposition 2.

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 capitalization level would become more sensitive to risks. Thus, monetary policy easing would lead to a larger reduction in risk-taking. To isolate the bank-specific factor Δ, we first consider a case where banks are homogeneous with identical Δ. These results are formally stated in the proposition below.

Proposition 3. Assume that banks are homogeneous with an identical Δ, the sensitivity of bank risk-taking to monetary policy shocks measured by $\frac{\partial \sigma}{\partial r}$ decreases with the tightness of capital requirements measured by ψ, but increases with the risk-weighting sensitivity measured by ρ. In particular, we have

$$\frac{\partial^2 \sigma}{\partial r \partial \psi} < 0, \quad \frac{\partial^2 \sigma}{\partial r \partial \rho} > 0. \tag{15}$$

Proof. See Supplemental Appendix A. □

In general, the impact of regulation changes (in particular, changes in the risk-weighting sensitivity ρ) on bank risk-taking depends on bank-specific risks Δ. All else being equal, a higher level of bank-specific risk implies a higher level of risk-weighted assets. To meet the CAR constraints, the bank would have to choose a lower-risk portfolio (i.e., a lower σ). Propositions 1 and 3 show that increasing the risk-weighting sensitivity (ρ) reduces risk-taking for all banks both on average (Eq (12)) and conditional on an expansionary monetary policy shock (Eq (15)). We now show that the effects of raising the risk-weighting sensitivity ρ on risk-taking are stronger for banks with higher levels of idiosyncratic risks Δ. These results are formally stated in the Proposition 4 below.

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

$$\frac{\partial^2 \sigma}{\partial \rho \partial \Delta} < 0. \tag{16}$$

Furthermore, 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 idiosyncratic risks reduces risk-taking more aggressively following an expansionary monetary policy shock. In particular, we have

$$\frac{\partial}{\partial \Delta} \left[\frac{\partial \sigma}{\partial r} \big|_{\rho=1} - \frac{\partial \sigma}{\partial r} \big|_{\rho=0} \right] > 0. \tag{17}$$

Proof. See Supplemental Appendix A. □

IV. Empirical analysis

The theoretical model predicts that increasing the sensitivity of risk-weighting reduces bank risk-taking, and risk-taking declines more for those banks facing higher idiosyncratic risks. 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 and we have obtained evidence that supports these 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).[10] 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 3,964,478 firm-year observations.[11] 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 dataset 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. *Credit ratings and loan ownership.* China's government has provided preferential credit access for SOEs (Song et al., 2011; Chang et al., 2016). Under such preferential

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[10]The "Big Five" banks play a dominant role in China's banking sector. They account for about half of China's bank lending in our sample period.

[11]Through 2007, the ASIF covered all SOEs regardless of their sizes, and large and medium-sized non-SOEs with annual sales above five million RMB. After 2007, the Survey excluded small SOEs with annual sales below five million RMB. After 2011, the ASIF included only manufacturing firms with annual sales above 20 million RMB.

TABLE 1. Credit Ratings and Loan Ownership

Credit Rating	Number	SOE Share	Amount	SOE Share
AAA	$4,426$	21.5%	$248,587$	63%
AA+	$7,213$	31.6%	$314,584$	56%
AA	$22,852$	21.8%	$515,173$	52%
AA-	$51,709$	8.2%	$632,094$	32%
A+	$52,555$	4.6%	$385,145$	22%
A	$25,927$	8.6%	$247,910$	28%
A-	$15,401$	2.8%	$105,009$	15%
BBB+	$14,264$	1.8%	$87,363$	9%
BBB	$9,825$	2.3%	$66,454$	22%
BBB-	$4,991$	0.8%	$35,511$	2%
BB	$9,573$	7.3%	$93,432$	22%
B	$59,594$	1.8%	$425,004$	5%

Notes: AAA to B correspond to the categories of credit ratings. The column of "Amount" is the total volume of loans (million Yuans).

policy, SOEs are considered safe borrowers. Our evidence shows that, all else being equal, SOE loans are more likely to receive high credit ratings.

Table 1 displays the credit rating and the share of SOE loans in each rating category. The credit rating includes 12 categories, ranging from AAA to B. For each individual loan, the bank identifies whether the borrower is an SOE or not. For each rating category, Table 1 reports the number and amount of loans and the corresponding SOE shares. The table shows that SOE loans account for the bulk of the high-quality loans. In particular, for loans rated AA or above, SOE loans account for 20-30% in terms of the number of loans and 50-60% in terms of the amount of loans. For loans with lower credit ratings, the SOE share is substantially smaller.

The positive relation between the credit rating and the SOE share of the loans is statistically significant and is not driven by time and location fixed effects or firm characteristics, as shown in Table 2. The table shows the estimation results when we regress credit ratings on the SOE loans, with or without controlling for time and location fixed effects and (potentially time-varying) firm characteristics. The dependent variable is the credit rating, taking values from 1 to 12, corresponding to the rate categories from B to AAA. The independent variable is a dummy indicator, which is equal to 1 if the borrower is an SOE and 0 otherwise. We estimated the empirical relation using both

TABLE 2. Credit Ratings and SOE Loans

Credit Rating	(1) OLS	(2) Ordered Probit	(3) Ordered Probit	(4) Ordered Probit
SOE loan	1.361***	0.884***	0.374***	0.509***
	(0.028)	(0.008)	(0.011)	(0.012)
Branch FE	yes	no	no	yes
Year-quarter FE	yes	no	yes	yes
Initial Controls × year FE	yes	no	yes	yes
R^2	0.262	–	–	–
Observations	241,688	264,213	241,688	241,688

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

an OLS specification and an ordered Probit model. In each case, we obtained a positive correlation between credit ratings and SOE shares, and the correlation is significant at the 99% confidence level.

IV.1.3. *Changes in banking regulations and bank risk-taking.* The Basel III regulations implemented in 2013 raised the minimum CAR from 8% to 10.5%. It has also introduced the IRB approach for weighting bank asset risks based on loan default probabilities and default exposures.[12]

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

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-quality 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, suggesting that the changes in capital regulations have contributed to changes in bank risk-taking. Furthermore, since SOE loans are correlated with high credit ratings (see Section IV.1.2), we should expect banks to increase the share of SOE lending (relative to trends) after 2013. Indeed, Figure 1 shows that the share of lending to SOEs has been declining before 2013, reflecting the underlying trend declines in the SOE sector in the economy.[13] After 2013, however, the share of SOE loans has stabilized, indicating that banks increased lending to SOEs relative to the long-term trend under the new capital regulations.

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 triple-difference empirical specification

$$SOE_{ijt} = \alpha \times RiskH_j \times Post_y + \beta \times RiskH_j \times Post_y \times MP_t$$
$$+ \gamma \times RiskH_j \times MP_t + \theta \times X_i \times \mu_y + \eta_j + \mu_t + \epsilon_{ijt}. \tag{18}$$

In this specification, the dependent variable SOE_{ijt} is a dummy variable that takes a value of one if the individual bank loan (indexed by i) is extended to an SOE firm by the city-level branch (indexed by j) in quarter t, and zero otherwise.

We interpret the implementation of Basel III regulations, and in particular, the changes in risk-weighting methods (from RW to IRB) as an exogenous event for bank branches.[14].

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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.

[13]Chang et al. (2016) document evidence that the share of SOE output in China's industrial revenue has declined steadily from about 50% in 2000 to about 30% in 2010, and further to about 20% in 2016.

[14]According to an internal document issued in 2012 by the bank from which we obtained the loan level data, the bank branches were required to implement the IRB risk-weighting approach, strengthen risk assessment, and improve controls of loan risks.

FIGURE 1. The Share of SOE Loans
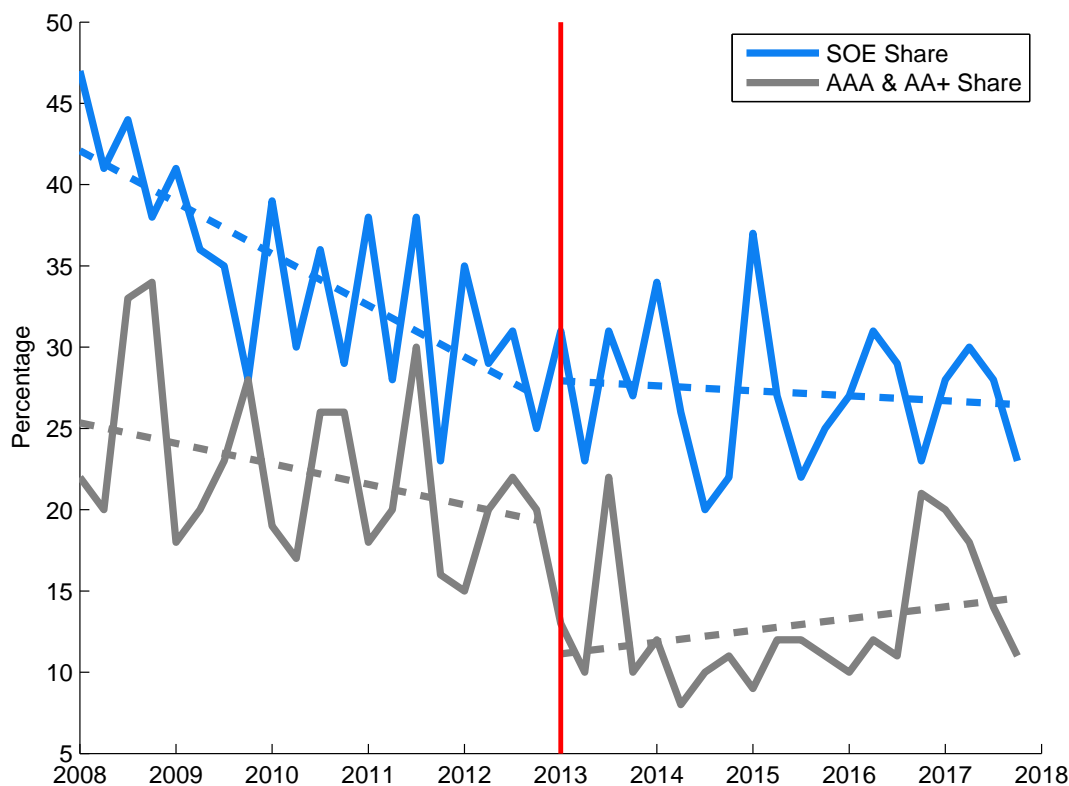
Notes: This figure shows the time series of the share of SOE loans to the total amount of loans (the blue line) and the share of high quality loans (i.e., those with credit ratings AA+ or AAA) in total loans (the gray line). The unit is percentage points. The dashed lines are linear fitted trend for the time series before or after 2013. The Bai-Perron test detects a significant structural break in 2013:Q1 in the trend of the share of high quality loans, although it does not detect a significant structural break in the share of SOE loans.

We use the dummy variable $Post_y$ to indicate the post-2013 periods under the new regulations: it equals one if the year is 2013 or after, and zero otherwise.

Our theoretical model suggests that the impact of changing the sensitivity to risk-weighting on bank risk-taking—both on average and conditional on monetary policy shocks—can vary across bank branches, depending on their idiosyncratic risks (see Proposition 4). In particular, high-risk bank branches should be more sensitive to regulation changes than low-risk branches. Based on this theoretical implication, we implement a difference-in-difference identification approach, exploiting the differential responses to regulation changes between the high-risk and the low-risk branches to identify the impact of regulation changes on risk-taking. We use the bank branches with a high average share of non-performing loans (NPLs) 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 the branch j's average share of NPL in the periods 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 share of non-performing loans. In our empirical specification (18), 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. The 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 behaviors of the treated group differed systematically from the control group before the new regulations were implemented. Table 3 compares several indicators of the lending behaviors 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 behaviors 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 behaviors following monetary policy shocks, we construct a measure of monetary policy shock (i.e., the term MP_t in Eq. (18)), which is the exogenous component of China's M2 growth, a quarterly time series estimated from the money growth rule using the regime-switching approach of Chen et al. (2018). 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 high-risk branches (Proposition 4). To capture these effects, we include the triple interaction term $RiskH_j \times Post_y \times MP_t$ in our empirical specification. The theory predicts that the coefficient on this triple interaction term should be positive (i.e., $\beta > 0$).

The variable X_i in Eq. (18) 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 equity (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

Table 3. Parallel trend test

Variables	(1) Low-risk group	(2) High-risk group	(3) Mean difference	(4) t-statistic	(5) p-value
SOE loan share	0.316	0.349	-0.033	-0.9256	0.355
AAA&AA+ loan share	0.097	0.068	0.028	1.3638	0.174
Small firm loan share	0.236	0.209	0.028	1.212	0.226
Averaged loan rate (%)	6.357	6.403	-0.046	-1.1523	0.250
log(Interest Income)	17.299	17.308	-0.009	-0.0589	0.953
log(loan amount)	20.057	20.049	0.008	0.0533	0.958
Loan-to-firm asset ratio	0.142	0.130	0.012	0.5455	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. Column (3) shows the difference between Columns (1) and (2). 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 non-performing loans in 2008-2012 exceeds the median. Otherwise, it is in the low-risk group. The loan amount, interest income, SOE loan share, AAA& AA+ loan share, and the 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 the volume-weighted average loan interest rates 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 then averaged across branches within each group.

initial conditions X_i with the year fixed effect μ_y.[15] The set of independent variables also include city (or equivalently, branch) fixed effect η_j and time (quarters) fixed effect μ_t. Finally, the term ϵ_{ijt} denotes the regression residual.[16] The parameter γ in Eq. 18 measures the average response of bank risk allocations to monetary policy shocks in the full sample. Our theory predicts that, under the new regulations with risk weighting (i.e, in the post-2013 periods), an expansionary monetary policy should raise bank leverage and reduce risk taking (see Proposition 2). However, before the introduction of the IRB

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

[16]In the empirical specification (18), 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. We do not include a firm fixed effect because the ownership structure of firms is fixed in our sample: SOEs remains state owned and private firms remain private.

approach in 2013, banks could not choose the risk weights on their assets based on credit risks. Thus, our theory has no clear predictions for the sign of γ.

Table 4 displays the summary statistics for the variables of interest in our analysis. The mean probability of SOE lending (the SOE dummy) is 5.9%, with a standard deviation of about 0.24. The average share of high-risk branches (the $RiskH$ dummy) before 2013 is about 51.4%, with a standard deviation of 0.5. The monetary policy shock (the term MP) has a mean of zero and a standard deviation of 0.007.

TABLE 4. Summary statistics

Variables	Obs.	Mean	Sta. Dev.	Min	Median	Max
SOE	333,500	0.059	0.235	0.000	0.000	1.000
$RiskH$	333,500	0.514	0.500	0.000	1.000	1.000
MP	333,500	0.000	0.007	-0.017	0.001	0.027

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

IV.3.1. *Baseline estimation results.* We use our micro-level data to estimate the baseline empirical model in Eq. (18). Table 5 reports the estimation results. Column (1) shows the OLS result. Consistent with our theory, the estimated values of both α and β are both positive and statistically significant.[17] The positive value of α suggests that, after implementing Basel III that increased the risk-weighting sensitivity, bank branches (especially those with risky balance sheets in the past) reduced their risk exposures by raising the share of SOE loans, which are considered safe lending because of their high credit ratings under government guarantees. The positive value of β implies that an expansionary monetary policy shock increases bank lending to SOEs after the implementation of the new regulations, but not before. Indeed, the estimated value of γ is statistically insignificant, indicating that a monetary policy shock by itself did not have a significant impact on bank 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).[18]

The point estimate of $\beta = 0.535$ implies that, for those bank branches with a high NPL ratio in the past, a one standard deviation increase in monetary policy shock

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[17]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 D.

[18]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 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 4).

(0.7%) would raise the probability of lending to SOEs by $0.535 \times 0.7\% = 0.37\%$. Since the sample average of the number of loans extended to SOEs is 5.9%, a one standard deviation increase in the monetary policy shock would thus raise the probability of SOE lending by $0.37/5.9 = 6.3\%$ relative the mean. 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 sensitivity to risk-weighting of bank assets can also affect risk-taking conditional on monetary policy shocks (Propositions 3 and 4).

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 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 need to control for the effects of changes in bank capitalization. For this purpose, we augment our baseline empirical specification (18) by including two additional controls that capture the effects of capitalization—the effective annual CAR of the bank (CAR_{y-1}) and the interactions between the effective CAR and monetary policy shocks ($MP_t \times CAR_{y-1}$)— both interacted with the $RiskH_j$ term. 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 periods, and then splice it with the CAR calculated based on the new IRB approach for the post-2013 periods.[19]

Table 5 reports the estimation results when the effects of capitalization are controlled for (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 (Column (3)),

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[19]The effective CAR is for the entire bank, from which we obtained the loan-level data. We do not have data to construct branch-level CARs.

Table 5. Effects of Regulations on Bank's Risk-Taking

$SOE_{i,j,t}$	(1) OLS	(2) Probit	(3) OLS	(4) Probit
$RiskH_j \times MP_t \times Post_y$	0.535**	0.452**	1.221***	0.929***
	(0.215)	(0.184)	(0.354)	(0.293)
$RiskH_j \times Post_y$	0.00712***	0.0058***	0.00411*	0.0025
	(0.00149)	(0.0014)	(0.00213)	(0.0021)
$RiskH_j \times MP_t$	-0.0185	-0.0598	6.137**	4.245*
	(0.172)	(0.125)	(2.415)	(2.287)
$RiskH_j \times MP_t \times CAR_{y-1}$			-0.487**	-0.339*
			(0.192)	(0.179)
$RiskH_j \times CAR_{y-1}$			0.00192*	0.0021**
			(0.00108)	(0.0011)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes
R^2	0.353		0.353	
Observations	333,500	315,382	333,500	315,382

Notes: Columns (1) and (2) report the estimation results in the baseline model, using OLS and the Probit, respectively. The monetary policy shock is constructed using the approach in Chen et al. (2018). The CAR for the pre-2013 periods is measured using the traditional RW approach, but for the post-2013 periods, it is measured using the new Internal Ratings Based (IRB) approach that increased the sensitivity of risk-weighted assets to loan risks. 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 interacted with the year fixed effects. 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.

the point estimate rises from the baseline value of 0.535 to 1.221.[20] The point estimate (1.221) implies that a one standard deviation monetary policy shock would increase the

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[20]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.

probability of SOE lending by about 14% (relative to the mean). We obtained similar results when we estimate the Probit model (see Column (4)).[21] Thus, consistent with our theory, the declines in bank risk-taking following a monetary policy expansion were primarily driven by changes in risk-weighting in the post-2013 period under the new regulations.

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 periods, but diverged after the new regulations were put in place.

To examine the validity of our parallel trends identification assumption, we estimate the empirical model

$$
\begin{aligned}
SOE_{i,j,t} \quad &= \sum_\tau \alpha_\tau \times RiskH_j \times \delta_\tau + \sum_\tau \beta_\tau \times RiskH_j \times \delta_\tau \times MP_t \\
&+ \gamma \times RiskH_j \times MP_t + \theta \times X_i \times \mu_y + \eta_j + \mu_t + \epsilon_{i,j,t},
\end{aligned} \tag{19}
$$

where $\tau \in \{2011, 2013, > 2013\}$ denotes the year, δ_τ is a dummy variable, which is equal to one in year τ and zero otherwise. The other variables have the same definitions as in the baseline model specified in Eq. (18), except that MP_t is demeaned by year. The parameter α_τ measures the relative risk-taking behavior of the treatment group in year τ, and the parameter β_τ measures the relative response of risk-taking to a monetary policy shock for the treatment group in year τ. Implicitly, the reference year is 2012. We consider the periods before the new regulations (2011), the year when the regulation was implemented (2013), and the years after the regulation shock.[22]

Figure 2 shows the point estimates of α_τ and β_τ along with the 95% confidence bands.[23] Since 2012 is the reference year, we normalize the values of both parameters to zero in that year. The figure shows that, in the pre-2013 periods, 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 the control group. The figure also shows that, since the regulation was implemented (2013 and after), the estimated values of α and β have 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

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[21]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.

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

[23]We report the full regression results in Supplemental Appendix C.

FIGURE 2. Parallel trends
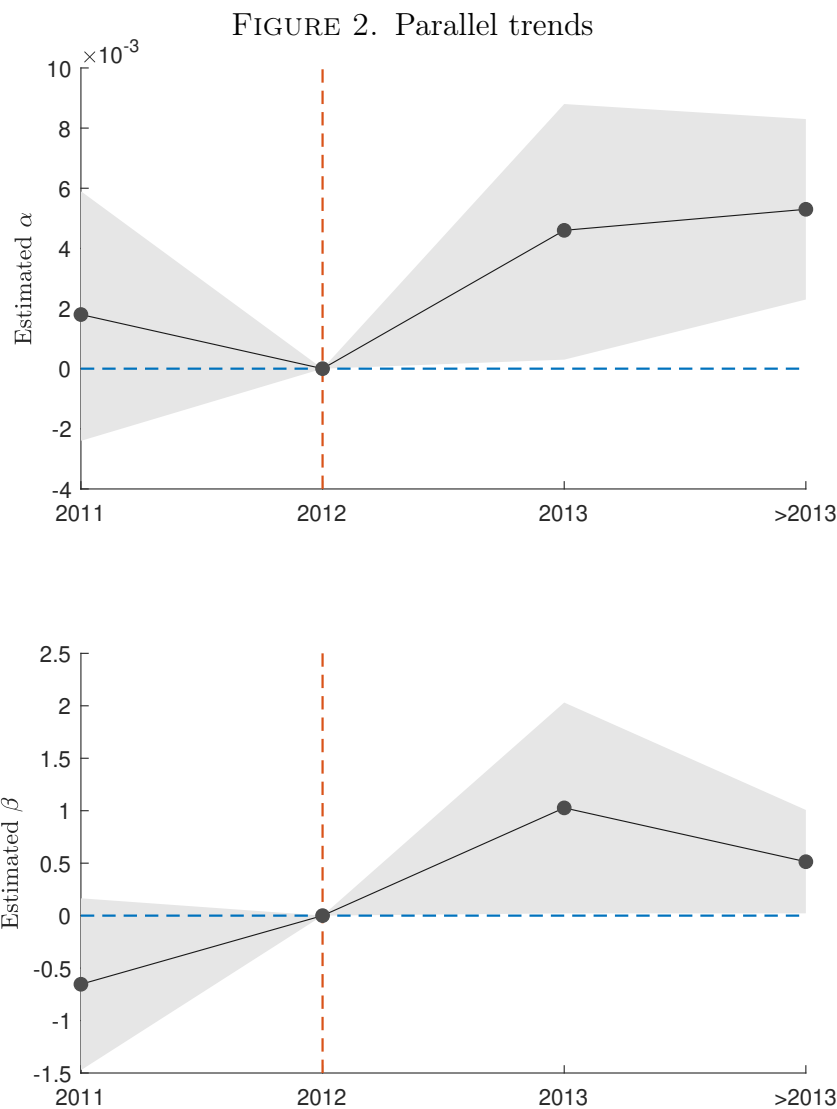
Notes: The figure shows the estimated coefficients α and β for the years 2011, 2013, and after 2013 from the empirical model in Eq. (19). The dots indicate the point estimates, and the shaded gray areas indicate the 95% confidence bands. The treatment group is the high-risk bank branches with average NPL ratios above the median in the pre-2013 period. The control group is 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.

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.

TABLE 6. Controlling for time-varying borrower characteristics

	(1) $LoanRate_{i,j,t}$	(2) $RateGap_{i,j,t}$	(3) $LoanRate_{i,j,t}$	(4) $RateGap_{i,j,t}$
$RiskH_j \times SOE_{i,t} \times MP_t \times Post_y$	-18.86**	-2.779**	-19.31**	-2.878**
	(9.169)	(1.407)	(9.233)	(1.435)
$RiskH_j \times MP_t \times Post_y$	15.58**	2.239*	15.70**	2.336*
	(6.309)	(1.174)	(6.467)	(1.208)
$RiskH_j \times SOE_{i,t} \times MP_t$	7.960*	1.597**	8.407*	1.609**
	(4.750)	(0.673)	(4.724)	(0.674)
$RiskH_j \times MP_t$	-15.34***	-2.186***	-15.33***	-2.180***
	(2.699)	(0.414)	(2.684)	(0.414)
$RiskH_j \times SOE_{i,t} \times Post_y$	-0.0115	0.00867	-0.0169	0.00806
	(0.0885)	(0.0142)	(0.0881)	(0.0143)
$RiskH_j \times SOE_{i,t}$	-0.281***	-0.0387***	-0.273***	-0.0381***
	(0.0541)	(0.00839)	(0.0538)	(0.00836)
$RiskH_j \times Post_y$	0.124	0.0235*	0.123	0.0238*
	(0.0781)	(0.0133)	(0.0780)	(0.0133)
$\ln(LoanAmount_{i,j,t})$			0.0102***	0.001***
			(0.0025)	(0.0003)
Observations	15,552	15,552	15,470	15,470
R-squared	0.966	0.937	0.966	0.937
Branch FE	yes	yes	yes	yes
Firm-Year-Quater FE	yes	yes	yes	yes

Notes: This table reports the estimation results using the subsample of firms that borrow from multiple bank branches. *LoanRate* is the loan interest rate (in %) on each loan. *RateGap* is the deviations of the loan rate from the benchmark loan rate. The monetary policy shock is constructed using the approach in Chen et al. (2018). Both models include controls for the branch fixed effects and the firm-year-quarter fixed effects. 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.

IV.3.4. *Controlling for loan demand factors.* Our baseline regression uses variations across time and across risk types of bank branches to identify the effects of changes in banking regulations and monetary policy. A potential concern is that increases in SOE lending in the post-2013 period might be driven by changes in loan demand of SOEs (relative to non-SOEs), instead of changes in lender decisions under the new regulations. This concern seems plausible, because China's economic growth has slowed during that period, discouraging production and investment activities of non-SOE firms.

To address this concern, we focus on the subsample of firms that borrow from multiple bank branches. This subsample allows us to control for time-varying borrower characteristics and therefore to isolate the effects of the policy changes through the loan supply channel. We use this subsample to estimate the impact of monetary policy shocks on the loan interest rate for different types of firms (SOE or non-SOE), before and after the implementation of Basel III. We use the same difference-in-difference identification approach as in the baseline case, exploiting the differences in the loan rates offered by high-risk vs. low-risk bank branches. Since we control for demand factors, changes in the loan rate should reflect changes in loan supply behaviors.

In the regression models that we consider here, the dependent variable is the firm-specific loan interest rate (denoted by $LoanRate_{i,j,t}$) offered to firm i by branch j in quarter t. We are interested in studying how a monetary policy shock affects the loan interest rates for an SOE firm relative to non-SOEs in the post-2013 period, and how the loan rate responses differ between high-risk and low-risk branches. This effect is captured by the coefficient on the quadruple interaction term $RiskH_j \times SOE_{i,t} \times MP_t \times Post_y$. Here, the term $SOE_{i,t}$ is a dummy variable, which equals one if firm i is an SOE firm and zero otherwise. The other variables are the same as defined in the baseline regression (18).

Table 6 displays the regression results. Column (1) shows that, controlling for the branch fixed effects and the firm-year-quarter fixed effects, an expansionary monetary policy shock in the post-2013 period leads to a significant decline in the loan interest rate offered by a high-risk branch to an SOE firm relative to non-SOEs (i.e., a negative coefficient on $RiskH_j \times SOE_{i,t} \times MP_t \times Post_y$). The point estimate implies that a positive one standard deviation monetary policy shock (0.007) reduces the loan rate for an SOE relative to non-SOEs by about 13 basis points ($-18.86 \times 0.007 \approx -0.13$). The same monetary policy shock raises the loan rate for a non-SOE firm (i.e., a positive coefficient on $RiskH_j \times MP_t \times Post_y$) by about 11 basis points ($15.58 \times 0.007 \approx 0.11$). These post-2013 lending behaviors of high-risk branches stand in contrast to those in the pre-2013 period. An expansionary monetary policy shock before 2013 raised the loan rate for SOEs and reduced that for non-SOEs for loans originated from high-risk

branches (i.e., the coefficient on $RiskH_j \times SOE_{i,t} \times MP_t$ is positive whereas that on $RiskH_j \times MP_t$ is negative). 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 SOEs, which are perceived as low-risk borrowers under government guarantees.[24]

These empirical patterns are robust to alternative measures of the loan costs. In particular, Column (2) in the table shows the regression results when we replace the loan interest rate $LoanRate_{i,j,t}$ by its deviations from the benchmark lending rate (denoted by $RateGap_{i,j,t}$). The qualitative results are the same. The results are also robust to controlling for the loan amount, as shown in Columns (3)-(4).

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

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

IV.4.1. *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 the loan interest rate, and allow banks to offer a range of interest rates that are within a narrow band of those benchmark rates. In 2013, the PBOC relaxed controls over bank lending rates. Subsequently, in 2015, the PBOC also widened the range of the deposit rates that banks can offer. These interest-rate liberalization policies might confound the effects of the Basel III regulatory regime.

To address this concern, we 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 deviations of the average lending interest rate across all loans from the benchmark lending rate in quarter t. A larger deviation from

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[24]The table also shows that, absent monetary policy shocks, there is no significant difference in the loan rates that a high-risk branch charged on loans to SOE borrowers vs. non-SOEs in the post-2013 period, although SOE borrowers faced a lower loan rate before 2013.

TABLE 7. Controlling for the impact of interest-rate liberalization

$SOE_{i,j,t}$	(1) OLS	(2) Probit
$RiskH_j \times MP_t \times Post_y$	0.708***	0.551***
	(0.223)	(0.190)
$RiskH_j \times Post_y$	0.00737***	0.0060***
	(0.00152)	(0.0014)
$RiskH_j \times MP_t$	0.213	0.1602
	(0.340)	(0.325)
$RiskH_j \times MP_t \times LoanRateGap_{t-1}$	-3.518	-2.857
	(3.121)	(3.148)
$RiskH_j \times LoanRateGap_{t-1}$	0.0624***	0.0424***
	(0.0185)	(0.0186)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls × year FE	yes	yes
R^2	0.350	0.510
Observations	330,473	312,053

Notes: Columns (1) and (2) report the results in OLS estimations , 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, the 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 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.

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 7 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 SOE 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 SOE lending (indicating more risk-taking), although this latter effect is insignificant.

After controlling for the effects of interest-rate liberalization, we still obtain large and significant impact of the new capital regulation regime for the risk-taking channel. After implementing the new regulations, high-risk branches increased their lending to SOEs in the post-2013 periods (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 is associated with changes in capital regulations; they are not driven by other reforms such as interest-rate liberalization.

IV.4.2. *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 regulation 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 behaviors. 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 8 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 SOEs in the post-2013 period, possibly in fear of being investigated.

However, adding controls for the anti-corruption effects does not affect our main empirical finding. As shown in Table 8, in the post-2013 period, high-risk branches are more likely to lend to SOEs, both on average and conditional on an expansionary monetary policy shock.

IV.4.3. *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

TABLE 8. Controlling for effects of anti-corruption campaigns

$SOE_{i,j,t}$	(1) OLS	(2) OLS
$RiskH_j \times MP_t \times Post_y$	0.550**	1.237***
	(0.215)	(0.353)
$RiskH_j \times Post_y$	0.00677***	0.00376*
	(0.00149)	(0.00213)
$RiskH_j \times MP_t$	-0.0295	6.136**
	(0.172)	(2.415)
$RiskH_j \times MP_t \times CAR_{y-1}$		-0.487**
		(0.192)
$RiskH_j \times CAR_{y-1}$		0.00192*
		(0.00108)
$AntiCorrup_j \times Post_y$	0.00673***	0.00672***
	(0.00154)	(0.00154)
$AntiCorrup_j \times MP_t$	0.207	0.204
	(0.174)	(0.174)
$AntiCorrup_j \times MP_t \times Post_y$	-0.319	-0.317
	(0.218)	(0.218)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls $\times$ year FE	yes	yes
R^2	0.354	0.354
Observations	333,500	333,500

Notes: $AntiCorrup_j$ is a dummy variable, which is equal to one if the bank branch is located in a city which belongs to 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 interacted with the year fixed effects. The numbers in the parentheses show the robust standard errors. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

crisis periods, but it has also led to a surge in leverage and over-investment, particular in those sectors with a high share of SOEs (Cong et al., 2019). In December 2015, the Chinese government implemented a deleveraging policy, aiming to reduce the leverage in the over-capacity industries. It is possible that the deleveraging policy might have played a role in driving the observed relation between bank risk-taking and monetary policy shocks.

To examine this possibility, we conduct a placebo test using China's deleveraging policy. We define a dummy variable, $DeLev_y$, which is equal to one if the year is 2016 or after, and zero otherwise. In the placebo test, we estimate the baseline empirical model (18), replacing the variable $Post_y$ in the baseline model with $DeLev_y$. Table 9 shows the estimation results. Unlike the banking regulation policy changes under Basel III, the deleveraging policy had no significant impact on bank risk-taking.

IV.4.4. *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 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.[25]

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 10 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 regulation changes raised the relative share of SOE lending by high-risk branches in response to a positive monetary policy shock.

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[25]The bank headquarter 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 9. Deleveraging Policy

$SOE_{i,j,t}$	(1) OLS	(2) OLS	(3) Probit	(4) Probit
$RiskH_j \times Delev_y$	0.001	0.001	0.002	0.016
	(0.002	(0.002)	(0.002)	(0.036)
$RiskH_j \times MP_t \times Delev_y$		0.150		-0.504
		(0.563)		(0.531)
$RiskH_j \times MP_t$		0.072		0.036
		(0.098)		(0.087)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial control $\times$ year FE	yes	yes	yes	yes
R^2	0.353	0.353	–	–
Observations	333,500	333,500	315,382	315,382

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 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 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.

IV.4.5. *Further robustness checks.* Our main empirical results are robust to alternative measurements, specifications, and controls. In particular, we have obtained similar results when we consider (1) clustering the standard errors at the bank branch and year-quarter level instead of computing robust standard errors, (2) using alternative definitions of SOEs, (3) using alternative measures of CAR, (4) using a measure of aggregate credit supply shocks instead of monetary policy shocks, and (5) using direct measures of IRB coverage instead of the post-2013 year dummy. To conserve space, we report these results in Supplementary Appendix D.

IV.5. **The macroeconomic implications of the risk-taking channel.** Our micro-level evidence shows that, under tightened capital regulations, a monetary policy expansion raises the share of bank lending to low-risk borrowers, and in particular, to SOEs.

Table 10. Additional Controls

$SOE_{i,j,t}$	(1) OLS	(2) OLS	(3) OLS	(4) Probit	(5) Probit	(6) Probit
$RiskH_j \times Post_y$	0.007***	0.006***	0.002	0.006***	0.005***	0.006***
	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
$RiskH_j \times MP_t \times Post_y$	0.541**	0.522**	0.688***	0.475***	0.453**	0.594***
	(0.215)	(0.214)	(0.203)	(0.184)	(0.184)	(0.188)
$RiskH_j \times MP_t$	-0.0178	-0.0268	-0.136	-0.0675	-0.066	-0.140
	(0.172)	(0.170)	(0.160)	(0.126)	(0.128)	(0.123)
$InitProfit_j \times$ year FE	yes	yes	yes	yes	yes	yes
$InitSOE_j \times$ year FE	no	yes	yes	no	yes	yes
Industry FE	no	no	yes	no	no	yes
Branch FE	yes	yes	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes	yes	yes
Initial controls $\times$ year FE	yes	yes	yes	yes	yes	yes
R^2	0.355	0.359	0.448	–	–	–
Observations	333,500	333,500	303,404	315,382	315,382	276,893

Notes: Columns (1)-(3) and (4)-(6) report the results in OLS and Probit estimations, respectively. 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 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 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.

In China, SOE loans receive high credit ratings because of government guarantees. Since SOEs have lower productivity than private firms, increasing lending to SOEs may worsen ex post loan performance and reduce aggregate productivity. We now provide evidence that supports this misallocation channel.

IV.5.1. *Ex post loan performance.* We measure the ex post loan performance by the NPL ratio of new loans or the share of overdue loans. Table 11 shows that, all else

TABLE 11. Ex Post Performances of SOE Loans

	(1) NPL OLS	(2) NPL Probit	(3) Overdue OLS	(4) Overdue Probit
SOE Loan	0.0286***	0.0197***	0.0121***	0.0290***
	(0.0021)	(0.0012)	(0.0019)	(0.0022)
Credit Rating	-0.0051***	-0.0056***	-0.0160***	-0.0149***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Branch FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Initial controls × year FE	yes	yes	yes	yes
R^2	0.075	–	0.111	–
Observations	241,688	225,845	241,086	236,923

Notes: This table reports the estimated ex post performance of SOE loans and loans with high credit ratings. The ex post performance is measured by either the NPL ratio of the new loans or the share of overdue loans. The variable NPL is a dummy that is equal to one if the status of the loan at end of the issue year is classified as "substandard," "doubtful," or "loss"; and it is zero otherwise. The variable Overdue is also a dummy that is equal to one if the loan is overdue or rolled over by the bank at the due time; and it is zero otherwise. The definitions of SOE Loan and Credit Rating are the same as those in Table 2. Columns (1) and (3) show the estimates of OLS, while Columns (2) 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 interacted with the year fixed effects. 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.

being equal, a new loan to an SOE tends to have a poorer ex post performance, with a higher probability of becoming non-performing or overdue. In contrast, a new loan with a high credit rating has better ex post performance. These results suggest that the ex ante high credit ratings of SOE loans mainly reflect government guarantees. When we control for the firm characteristics and the credit ratings, SOE loans tend to have poor ex post performance. Thus, by raising the share of new loans to SOEs, a monetary policy expansion can contribute to credit misallocation.

IV.5.2. *Total factor productivity (TFP).* Empirical studies show that SOEs in China have lower average productivity than private firms Hsieh and Klenow (2009). Thus, by inducing banks to raise the share of SOE lending, the implementation of the Basel III regulations may have reduced aggregate productivity. To examine this possibility, we compute a measure of TFP using the province-level data based on the approach in (Brandt et al., 2013).[26]

Table 12 shows that estimation results for two empirical specifications. In the first specification (Columns (1)-(2)), the provincial TFP growth rates depend on the post-2013 dummy $Post_y$, the monetary policy shock MP_t, and the interactions between these two variables. In the second specification (Columns (3)-(4)), we consider a measure of average risk exposures of bank branches at the province level (denoted by $RiskH_p$), and include the interactions between the three variables of interest ($Post_y$, MP_t, and $RiskH_p$). In all regressions, we control for province fixed effects. Compared to the baseline case in Column (1), the regressions in Columns (2)-(4) include additional controls for provincial characteristics such as the province's human capital, openness to trade, and aged population share.

A coherent pattern from these alternative empirical specifications emerges: in the post-2013 periods, an expansionary monetary policy reduced province-level TFP growth significantly, especially for those provinces with high-risk bank branches. For example, focusing Column (4), which includes the risk exposure measure $RiskH_p$ and year fixed effects, the point estimates of the coefficients imply that a one standard deviation positive shock to monetary policy in the post-2013 period reduces provincial TFP growth by about 1.14 percentage points.[27] Our finding here suggests that the new capital regulations, by raising the share of bank lending to SOEs, have contributions to aggregate productivity slowdown in response to expansionary monetary policy shocks.

V. 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 SOEs, both on average and conditional on monetary policy expansions. The declines in bank risk-taking following a monetary policy

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[26]See Supplementary Appendix B for some details of our calculations of the province-level TFP.

[27]In our sample, the standard deviation of the monetary policy shock is about 0.28% (at the annual frequency). Thus, the point estimate of -4.077 for the term $MP_t \times Post_y \times RiskH_p$ implies a reduction in TFP growth of $4.077 \times 0.28\% \approx 1.14\%$.

TABLE 12. Effects of Regulation Changes on Provincial TFP Growth Rates

	(1) TFP Growth	(2) TFP Growth	(3) TFP Growth	(4) TFP Growth
$MP_t \times Post_y$	-9.688***	-8.760***	-8.169***	
	(1.197)	(1.191)	(1.352)	
$MP_t \times Post_y \times RiskH_p$			-4.550**	-4.077*
			(1.850)	(2.055)
$Post_y$	-0.0298***	-0.0351***	-0.0387***	
	(0.00589)	(0.00631)	(0.00679)	
MP_t	2.847***	3.350***	2.254**	
	(0.988)	(0.975)	(0.930)	
$Post_y \times RiskH_p$			0.0274**	0.0292**
			(0.0129)	(0.0107)
$MP_t \times RiskH_p$			8.189***	8.297***
			(1.792)	(1.638)
Year FE	no	no	no	yes
Controls	no	yes	yes	yes
Province FE	yes	yes	yes	yes
Observations	300	287	287	287
R^2	0.288	0.375	0.391	0.557

Notes: This table reports the estimated effects of banking regulations on the provincial TFP growth rates. The data used are a province-year panel, covering all 30 provinces/regions for the 10 year period from 2008 to 2017. The dependent variable is the provincial TFP growth rate, calculated using the approach in Brandt et al. (2013). The province-level risk exposures $RiskH_p$ is measured by a dummy, which is equal to one if all branches located in the province are of the high-risk type (i.e., with NPL ratios above the median). The other variables (MP_t and $Post_y$) have the same definitions as those in the baseline estimation. In all columns, we include controls for the province fixed effects. In Columns (2)-(4), we add additional controls for a set of provincial characteristics, including the number of high school students/population, (imports+exports)/GDP, and aged population share. All the provincial data are obtained from the WIND database. In Column (4), we include controls for the year fixed effects. The numbers in the parentheses show the 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.

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 SOE lending by up to 14% after the new regulations were put in place in 2013.

In China, banks can reduce their loan risks by shifting lending to SOEs, because SOE loans receive high credit ratings under government guarantees. However, SOEs have lower average productivity than private firms. Thus, increasing lending to SOEs reduces aggregate productivity. Our evidence supports this reallocation channel.

Although our data are from China, the general implications of our findings for the interconnection between monetary policy, bank risk-taking, and capital allocation efficiency are not specific to that country. Our evidence suggests that changes in capital regulations that increase the sensitivity of risk weighting helps 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 misallocations that depress aggregate productivity. The tradeoff between bank risk-taking and capital misallocations identified in our study is likely to play an important role for designing optimal macroeconomic stabilization policies.

APPENDIX: 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%. Banks should also
hold a countercyclical capital buffer, the size of which varies between 0 and 2.5% of
risk-weighted assets.[28]

The implementation of Basel III regulation in China not just 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 risks.[29] 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*.[30] The IRB approach assigns risk weights to loans based on their credit
risks. A loan with a higher credit rating would receive a lower risk weight.[31] All else
being equal, SOE loans receive higher credit ratings than private firms. Thus, the IRB
approach assigns a lower risk weight on 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

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[28]For systemically important banks, the minimum CAR was raised to 11.5%. For more details about
the new regulation, see

http://www.cbrc.gov.cn/EngdocView.do?docID=86EC2D338BB24111B3AC5D7C5C4F1B28.

[29]For example, the risk weight on a commercial bank's claims on corporates is 100%, regardless of
the firms' credit rating.

[30]The CBRC encourages commercial banks to adopt the Internal Ratings Based Approach when
evaluating risk-weighted assets. According to the regulation, the commercial bank can apply to the
CBRC for adopting the Internal Ratings Based Approach. The minimal requirement for the applicant
bank is that the coverage of the Internal Ratings Based Approach should be no less than 50% of the
total risk-weighted assets, and this ratio must be achieved 80% within three years.

[31]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 (PD), loss at given default (LGD),
exposure at default (EAD), correlation and maturity (M) of each individual exposure.

release an annual report of their CARs, with different definitions: one based on the pre-2013 Regulatory Weighting (RW) approach, and the other on the new IRB approach. The difference between the effective CAR calculated based on these two different approaches is illustrated by Table 13, 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 13. 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 Internal Ratings Based (IRB) approach to assess risk-weighted assets for 2014 and Regulatory Weighting (RW) approach for 2013.

References

Adrian, T. and H. S. Shin (2010). Financial intermediaries and monetary economics. In B. M. Friedman and M. Woodford (Eds.), *Handbook of Monetary Economics*, Volume 3, Chapter 12, pp. 601–650. Elsevier.

Allen, F., Y. Qian, G. Tu, and F. Yu (2019, July). Entrusted loans: A close look at China's shadow banking system. *Journal of Financial Economics 133*(1), 18–41.

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

Bernanke, B. S. (2020, January). The new tools of monetary policy. American Economic Association Presidential Address.

Bianchi, J. and S. Bigio (2017). Banks, liquidity management, and monetary policy. Unpublished Manuscript, Federal Reserve Bank of Minneapolis and UCLA.

Bleck, A. and X. Liu (2018). Credit expansion and credit misallocation. *Journal of Monetary economics 94*, 27–40.

Bonfim, D. and C. Soares (2018). The risk-taking channel of monetary policy: Exploring all avenues. *Journal of Money, Credit and Banking 50*(7), 1507–1541.

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

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

Brunnermeier, M. K., M. Sockin, and W. Xiong (2020, May). China's model of managing the financial system. NBER Working Paper No. 27171.

Bruno, V. and H. S. Shin (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics 71*, 119–132.

Chang, C., K. Chen, D. F. Waggoner, and T. Zha (2016). Trends and cycles in China's macroeconomy. In M. Eichenbaum and J. A. Parker (Eds.), *NBER Macroeconomics Annual 2015*, Volume 30, pp. 1–84. Chicago: University of Chicago Press.

Chang, C., Z. Liu, M. M. Spiegel, and J. Zhang (2019, May). Reserve requirements and optimal chinese stabilization policy. *Journal of Monetary Economics 103*, 33–51.

Chen, K., J. Ren, and T. Zha (2018). The nexus of monetary policy and shadow banking in China. *American Economic Review 108*(12), 3891–3936.

Chen, K., Q. Wang, T. Xu, and T. Zha (2020, July). Aggregate and distributional impacts of housing policy: China's experiment. Unpublished Manuscript.

Chen, Z., Z. He, and C. Liu (2020). The financing of local government in China: Stimulus loan wanes and shadow banking waxes. *Journal of Financial Economics 137*, 42–71.

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

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

Dell'Ariccia, G., L. Laeven, and R. Marquez (2014). Monetary policy, leverage, and bank risk-taking. *Journal of Economic Theory 149*, 65–99.

Dell'Ariccia, G., L. Laeven, and G. A. Suarez (2017). Bank leverage and monetary policy's risk-taking channel: evidence from the united states. *Journal of Finance 72*(2), 613–654.

Gao, H., H. Ru, R. M. Townsend, and X. Yang (2019, May). Rise of bank competition: Evidence from banking deregulation in China. NBER Working Paper No. 25795.

Geng, Z. and J. Pan (2019, December). The SOE premium and government support in China's credit market. NBER Working Paper No. 26575.

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

Hsieh, C.-T. and Z. M. Song (2015, March). Grasp the large, let go of the small: The transformation of the state sector in China. In J. C. Eberly and J. H. Stock (Eds.), *Brookings Papers on Economic Activity*, Volume Spring, pp. 295–366. The Brookings Institution.

Huang, Y., M. Pagano, and U. Panizza (2020). Local crowding out in China. *Journal of Finance (forthcoming)*.

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

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American Economic Review 80*(5), 1183–1200.

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

Liu, Z., P. Wang, and Z. Xu (2020). Interest-rate liberalization and capital misallocations. *American Economic Journal: Macroeconomics (forthcoming)*.

Maddaloni, A. and J.-L. Peydró (2011). Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the euro-area and the us lending standards. *the review of financial studies 24*(6), 2121–2165.

Reis, R. (2013). The portugese slump and crash and the euro crisis. *Brookings Papers on Economic Activity 44*(1), 143–210.

Song, Z., K. Storesletten, and F. Zilibotti (2011). Growing like China. *The American Economic Review 101*(1), 196–233.

Song, Z. M. and W. Xiong (2018). Risks in China's financial system. *Annual Review of Financial Economics 10*(261-286).

Stein, J. C. (2013, February). Overheating in credit markets: Origins, measurement, and policy responses. 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, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *American Economic Review 71*(3), 393–410.

Sun, G. (2019). China's shadow banking: Bank's shadow and traditional shadow banking. BIS Working Papers 822, Bank for International Settlements.

Zentefis, A. K. (2020). Bank net worth and frustrated monetary policy. *Journal of Financial Economics 138*, 687–699.

Supplemental Appendices: For Online Publication

APPENDIX A. PROOFS

This section provides the proofs of the propositions in Section III.

Proof of Proposition 1.

Proof. The optimizing condition (11) can be written as

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

where

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

Therefore, $g\left(\sigma;r,\Delta\right) = 0$ is equivalent to $\upsilon\left(\sigma;r,\Delta\right) = 0$.

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

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

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

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

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

$$\upsilon_\sigma \leq -\left(1 - \rho\right)\left(\phi_1 + \frac{1}{2}\Delta\right) - \left(1 - \rho\right)\rho r\psi\Delta^\rho\sigma^{\rho-1} < 0. \qquad (A.3)$$

We also have

$$\upsilon\left(\hat{\sigma};r,\Delta\right) = \left(1 + \rho\right)r - \left(1 - \rho\right)r\psi\Delta^\rho\hat{\sigma}^\rho > 2\rho r > 0, \qquad (A.4)$$

and

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

$$= -\rho\left[\bar{R}\left(\sigma,\Delta\right) - r\right] - \left(1 - \rho\right)r\psi\Delta^\rho\bar{\sigma}^\rho < 0. \qquad (A.5)$$

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

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

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

$$\upsilon_\rho = \phi_2\sigma^2 - (\phi_1 + \frac{1}{2}\Delta)\sigma + r + r\psi\left(\sigma\Delta\right)^\rho - (1-\rho)r\psi\left(\sigma\Delta\right)^\rho\log\left(\sigma\Delta\right)$$

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

$$< -\frac{1}{\rho}\left[-3\phi_2\sigma^2 + (\phi_1 + \frac{1}{2}\Delta)\sigma + R^*\left(\sigma, \Delta\right)\right] < 0$$

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

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

Finally, we show that $\frac{\partial \sigma}{\partial \Delta} > 0$. Applying the implicit function theorem to the optimal condition $\nu\left(\sigma; r, \Delta\right) = 0$ yields

$$\frac{\partial \sigma}{\partial \Delta} = -\frac{\nu_\Delta}{\nu_\sigma}$$

$$= -\frac{(1-\rho)}{2\nu_\sigma}\left(\sigma - 2\rho r\psi\Delta^{\rho-1}\sigma^\rho\right)$$

$$= -\frac{(1-\rho)}{2\nu_\sigma\Delta\lambda}\left(\lambda\Delta\sigma - 2\rho r\right)$$

$$> -\frac{(1-\rho)}{2\nu_\sigma\Delta\lambda}\left(\frac{1}{\psi} - 2\rho r\right) > 0,$$

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

$\square$

Proof of Proposition 2.

Proof. Applying the implicit function theorem to $\upsilon\left(\sigma; r, \Delta\right) = 0$ yields

$$\frac{d\sigma}{dr} = -\frac{\upsilon_r}{\upsilon_\sigma} = -\frac{(1+\rho) - (1-\rho)\psi\left(\sigma\Delta\right)^\rho}{\upsilon_\sigma}, \quad (A.6)$$

where υ_σ is given by (A.3). The second equality is from the definition of υ_r. Notice that under the binding CAR constraint, we have $\lambda = \frac{1}{\psi(\sigma\Delta)^\rho} > 1$ and $\upsilon_\sigma < 0$, therefore $(1+\rho) - (1-\rho)\frac{(\sigma\Delta)^\rho}{\psi} > 0$ implying $\frac{d\sigma}{dr} > 0$. Moreover, from the CAR constraint we have

$$\frac{d\lambda}{dr} = -\frac{\rho}{\psi\Delta^\rho\sigma^{\rho-1}}\frac{d\sigma}{dr} < 0. \quad (A.7)$$

$\square$

Proof of Proposition 3.

Proof. Without loss of generality, we assume $\Delta = 1$. The proof proceeds similarly for any $\Delta > 1$. We first show that $\frac{\partial^2 \sigma}{\partial r \partial \psi} < 0$, which is equivalent to

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

The last line is obtained with v_σ given by (A.3). To further simplify the last equation, from $v(\sigma; r, \psi) = 0$, we have

$$
-(3-\rho)\phi_2\sigma = -\frac{(1+\rho)r}{\sigma}\left(1 - \frac{1-\rho}{1+\rho}\psi\sigma^\rho\right) - (1-\rho)\left(\phi_1 + \frac{1}{2}\right). \tag{A.8}
$$

Therefore, $\frac{\partial^2 \sigma}{\partial r \partial \psi}$ can be further expressed as

$$
\frac{\partial^2 \sigma}{\partial r \partial \psi} = -\frac{1-\rho}{v_\sigma^3}\sigma^\rho \Psi, \tag{A.9}
$$

where

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

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

$$
\Psi = -(3-\rho)\phi_2\sigma\left[(3-\rho)\phi_2\sigma + \frac{\rho(1+\rho)r}{\sigma}\right] - (1+\rho)\frac{r}{\sigma}\left(1 - \frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\Xi, \tag{A.10}
$$

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

Therefore, we obtain

$$\Xi > (3 - \rho)\phi_2(\rho + 1)\sigma - (1 - \rho)(1 + \rho)\left(\phi_1 + \frac{1}{2}\right) > 0, \qquad\text{(A.11)}$$

which implies that $\Psi < 0$, and thereby $\frac{\partial^2 \sigma}{\partial r \partial \psi} < 0$.

We next show that $\frac{\partial^2 \sigma}{\partial r \partial \rho} > 0$, which is equivalent to

$$\frac{\partial}{\partial \rho}\left[\frac{\partial \sigma}{\partial r}\right] = -\frac{\partial}{\partial \rho}\left[\frac{v_r}{v_\sigma}\right] = -\frac{v_{r\rho} + v_{r\sigma}\frac{d\sigma}{d\rho}}{v_\sigma} + \frac{v_r}{v_\sigma^2}\left[v_{\sigma\rho} + v_{\sigma\sigma}\frac{d\sigma}{d\rho}\right]$$

$$= \frac{v_{r\sigma}v_\rho + v_{\sigma\rho}v_r - v_{r\rho}v_\sigma}{v_\sigma^2} - \frac{v_r v_\rho v_{\sigma\sigma}}{v_\sigma^3} > 0$$

where

$$v_\sigma = -2(3 - \rho)\phi_2\sigma + (1 - \rho)(\phi_1 + \frac{1}{2}) - \rho(1 - \rho)r\psi\sigma^{\rho-1} < 0$$

$$v_r = (1 + \rho) - (1 - \rho)\psi\sigma^\rho > 0$$

$$v_\rho = \phi_2\sigma^2 - (\phi_1 + \frac{1}{2})\sigma + r + r\psi\sigma^\rho - (1 - \rho)r\psi\sigma^\rho \log \sigma < 0$$

$$v_{r\sigma} = -\rho(1 - \rho)\psi\sigma^{\rho-1} < 0$$

$$v_{r\rho} = 1 + \psi\sigma^\rho - (1 - \rho)\psi\sigma^\rho \log \sigma > 0$$

$$v_{\sigma\rho} = 2\phi_2\sigma - (\phi_1 + \frac{1}{2}) - (1 - 2\rho)r\psi\sigma^{\rho-1} - \rho(1 - \rho)r\psi\sigma^{\rho-1} \log \sigma$$

$$v_{\sigma\sigma} = -2(3 - \rho)\phi_2 + \rho(1 - \rho)^2 r\psi\sigma^{\rho-2}$$

First,

$$v_{\sigma\sigma} = -2(3 - \rho)\phi_2 + \rho(1 - \rho)^2 r\psi\sigma^{\rho-2} < -2(3 - \rho)\phi_2 + \rho(1 - \rho)^2\frac{r}{\sigma}\psi\sigma^\rho\frac{1}{\widehat{\sigma}}$$

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

$$= -(3 - \rho)\phi_2\left[2 - \rho(1 - \rho)\frac{r}{\sigma}\psi\sigma^\rho\frac{1}{(\phi_1 + \frac{1}{2})}\right] < 0$$

Second,

$$v_{r\sigma}v_\rho + v_r v_{\sigma\rho} - v_\sigma v_{r\rho}$$

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

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

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

$$= 8\phi_2\sigma - 2\left(\phi_1 + \frac{1}{2}\right) + (1 - \rho)(1 + \rho)\psi\sigma^\rho\left[\left(\phi_1 + \frac{1}{2}\right) - \frac{2 + \rho}{1 + \rho}\phi_2\sigma - \frac{r}{\sigma}\left(1 - \frac{1 - \rho}{1 + \rho}\psi\sigma^\rho\right)\right]$$

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

$$= 8\phi_2\sigma - 2\left(\phi_1 + \frac{1}{2}\right) + (1-\rho)\psi\sigma^\rho\left[2(\phi_1 + \frac{1}{2}) - 5\phi_2\sigma\right]$$

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

$$> 0$$

The last inequality requires

$$\left[8 - 5(1-\rho)\psi\sigma^\rho\right]\phi_2\sigma - 2\left[1 - (1-\rho)\psi\sigma^\rho\right]\left(\phi_1 + \frac{1}{2}\right) > 0$$

A sufficient condition

$$\left[8 - 5(1-\rho)\psi\sigma^\rho\right]\phi_2\widehat{\sigma} - 2\left[1 - (1-\rho)\psi\sigma^\rho\right](\phi_1 + \frac{1}{2}) > 0$$

$$(1-\rho)\left[8 - 5(1-\rho)\psi\sigma^\rho\right] - 2(3-\rho)\left[1 - (1-\rho)\psi\sigma^\rho\right] > 0$$

$$2(1-3\rho) + \psi\sigma^\rho(1-\rho)(1+3\rho) > 0$$

which holds for relatively small ρ.

Thus, we obtain

$$\frac{\partial}{\partial\rho}\left[\frac{\partial\sigma}{\partial r}\right] = \frac{v_{r\sigma}v_\rho + v_{\sigma\rho}v_r - v_{r\rho}v_\sigma}{v_\sigma^2} - \frac{v_r v_\rho v_{\sigma\sigma}}{v_\sigma^3} > 0$$

□

Proof of Proposition 4.

Proof. We first prove $\frac{\partial^2\sigma}{\partial\Delta\partial\rho} < 0$. It is equivalently to show

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

From the proof in Proposition 1, we can derive $v_{\rho\sigma}$, v_Δ, $v_{\sigma\Delta}$ and $v_{\sigma\sigma}$. Then, we can further write

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

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

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

Therefore, we obtain

$$
v_{\rho\sigma}v_\Delta + v_\rho v_{\sigma\Delta} - v_{\rho\Delta}v_\sigma - v_\rho v_\Delta \frac{v_{\sigma\sigma}}{v_\sigma}
$$

$$
< -\frac{(1-\rho)}{2}\sigma v_\rho \frac{v_{\sigma\sigma}}{v_\sigma} + \frac{(1-\rho)}{2}\left[3\phi_2\sigma^2 - \left(\phi_1 + \frac{1}{2}\Delta\right)\sigma + r\right] - (3-\rho)\phi_2\sigma^2
$$

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

$$
+ \frac{6\rho r\phi_2\sigma}{(1-\rho)} + \frac{(1+\rho)r}{2}\left(\phi_1 + \frac{1}{2}\Delta\right) - r\psi\Delta^\rho\sigma^{\rho-1}\frac{(2-\rho)(1-\rho)}{2}\rho r
$$

$$
+ r\psi\Delta^\rho\sigma^{\rho-1}\left[\left((3-\rho)\phi_2\sigma^2 - \frac{(1-\rho)^2}{2}\rho r\psi\Delta^\rho\sigma^\rho\right)(1-(1-\rho)\log(\Delta\sigma))\right.
$$

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

$$
< 0.
$$

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

$$
\frac{6\rho r\phi_2\sigma}{(1-\rho)} - r\psi\Delta^\rho\sigma^{\rho-1}\frac{(2-\rho)(1-\rho)}{2}\rho r > 6\rho r\frac{\phi_1 + \frac{1}{2}\Delta}{3-\rho} - \frac{r}{\lambda\sigma}\frac{(2-\rho)(1-\rho)}{2}\rho r
$$

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

and

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

$$
> (1-\rho)\left[\bar R(\sigma,\Delta) - \frac{\rho(1-\rho)}{2}r\right] > (1-\rho)r\left[1 - \frac{\rho(1-\rho)}{2}\right] > 0.
$$

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

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

In the case of $\rho = 1$, the effect of interest rate on bank risk-taking is

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

which does not depend on the bank's ability of risk management, Δ.

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

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

which is increasing in the bank-specific risk Δ. $\qquad\square$

Appendix B. Procedure for Calculating Provincial TFP

We follow the approach in Brandt et al. (2013) to calculate the yearly provincial TFP. The production function is assumed to take the Cobb-Douglas form with constant return to scale, $Y_{it} = A_{it}K_{it}^{\alpha}L_{it}^{1-\alpha}$, where subscript i and t represent province ID and year, respectively; Y_{it} is the output; A_{it} is the provincial TFP; K_{it} and L_{it} are capital stock and labor input, respectively.

We set 2001 as the baseline year. We first construct capital stock series through a perpetual inventory method based on the annual fixed investment data reported by the National Bureau of Statistics. The investment flow is deflated using official province-level price indices of investment goods. Assuming a depreciation rate of 10% , we firstly calculated the initial capital stock at the year of 2001, as fixed investment of 2001 divided by depreciation rate. Then we calculate the capital stock for the consequent years according to the capital accumulation equation.

Real provincial GDP is deflated by the provincial GDP deflator, which is derived from the nominal and real provincial GDP growth rates. We use the employment number of each province as the labor input.

We then estimate the production function through the following regression equation

$$\ln \frac{Y_{it}}{L_{it}} = \gamma + \alpha \ln \frac{K_{it}}{L_{it}} + \varepsilon_{it}. \tag{B.1}$$

We obtain the estimated α of 0.67 at the 1% significance level. Then we calculate the provincial TFP at year t as

$$\ln A_{it} = \ln Y_{it} - \hat{\alpha} \ln K_{it} - (1 - \hat{\alpha}) \ln L_{it}, \tag{B.2}$$

where $\hat{\alpha} = 0.67$. The TFP growth rate is defined as $\Delta A_{it} = \ln A_{it} - \ln A_{it-1}$. The TFP growth rate calculated using our approach is highly correlated with that obtained by Brandt et al. (2013) over the same sample periods, with a correlation coefficient of 0.77.

Appendix C. Regression results for the parallel trends test

Table C.1 shows the regressions results for the parallel trend test.

TABLE C.1. Parallel trends regression

$SOE_{i,j,t}$	(1) OLS
$RiskH_j \times Year = 2011$	0.0018
	(0.0021)
$RiskH_j \times Year = 2013$	0.0046**
	(0.0022)
$RiskH_j \times Year > 2013$	0.0053***
	(0.0015)
$RiskH_j \times MP_t \times Year = 2011$	-0.6539
	(0.4179)
$RiskH_j \times MP_t \times Year = 2013$	1.0268**
	(0.5124)
$RiskH_j \times MP_t \times Year > 2013$	0.5145**
	(0.2513)
$RiskH_j * MP_t$	-0.0151
	(0.2041)
Branch FE	yes
Year-quarter FE	yes
Initial controls $\times$ year FE	yes
R^2	0.354
Observations	333,500

Notes: The table reports the estimation of parallel trends with the empirical speci-
fication (19). The monetary policy shock is constructed using the approach in Chen
et al. (2018), and demeaned by year. 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 interacted with the year fixed effects.
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.

APPENDIX D. FURTHER ROBUSTNESS CHECKS

This section reports the results from a few robustness checks.

TABLE D.1. Clustered standard errors

$SOE_{i,j,t}$	(1) OLS	(2) OLS
$RiskH_j \times MP_t \times Post_y$	1.221**	1.221**
	(0.480)	(0.523)
$RiskH_j \times Post_y$	0.00411	0.00411
	(0.00666)	(0.00681)
$RiskH_j \times CAR_{y-1} \times MP_t$	-0.487**	-0.487*
	(0.227)	(0.262)
$RiskH_j \times CAR_{y-1}$	0.00192	0.00192
	(0.00271)	(0.00250)
$RiskH_j \times MP_t$	6.137**	6.137*
	(2.919)	(3.294)
Double-Clustered at	Branch & Year-quarter	Firm & Year-quarter
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls $\times$ year FE	yes	yes
R^2	0.353	0.353
Observations	333,500	333,500

Notes: The numbers in the parentheses indicate robust standard errors. The numbers in the parentheses show the robust standard errors double clustered at branch (firm) and year-quarter levels. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

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 D.1 below.

Alternative definitions of SOEs. In the baseline estimation, we identify the ownership of the individual loans according to the bank's own definition. Here, we consider two alternative definitions of SOEs using the firm-level information in the ASIF: one using the registration type of the firm, and the other using the ownership controls (administrative subordinations). We re-estimate our baseline model using these alternative SOE

TABLE D.2. Alternative Definitions of SOEs

$SOE_{i,j,t}$	(1)	(2)	(3)	(4)
	SOE 1		SOE 2	
	OLS	Probit	OLS	Probit
$RiskH_j \times MP_t \times Post_y$	0.275*	0.276*	0.512***	0.871***
	(0.142)	(0.151)	(0.151)	(5.494)
$RiskH_j \times Post_y$	0.0025***	0.0025**	0.0076***	-0.0005
	(0.0010)	(0.0011)	(0.0010)	(0.0012)
$RiskH_j \times MP_t$	-0.220*	-0.317***	-0.136	-0.132
	(0.116)	(0.098)	(0.123)	(0.103)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial control × year FE	yes	yes	yes	yes
R^2	0.238	–	0.244	–
Observations	333,500	248,450	295,729	193,814

Notes: Columns (1)-(2) and (3)-(4) respectively report the results in OLS and Probit estimations for two alternative definitions of SOEs using the information in ASIF. "SOE 1" corresponds to the definition based on the registration type, and "SOE 2" corresponds to the definition based on ownership controls (administrative subordinations). All the 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 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 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.

definitions. Table D.2 shows that the main results obtained in our baseline regressions are not sensitive to these alternative SOE definitions.

Alternative measures of CAR. Our results are also robust to alternative measures of the CAR, as shown in Table D.3.

Aggregate credit supply shocks. Under given capital regulations, a bank needs to reduce risk-taking if its leverage increases. An increase in bank leverage can be caused by an increase in money supply, as we have examined, or by an increase in the supply

TABLE D.3. Alternative Measures of CAR

$SOE_{i,j,t}$	(1) CAR1	(2) CAR2	(3) CAR3
$RiskH_j \times MP_t \times Post_y$	0.449**	1.016***	0.492**
	(0.216)	(0.359)	(0.215)
$RiskH_j \times Post_y$	0.00750***	0.00442**	0.00699***
	(0.00151)	(0.00217)	(0.00150)
$RiskH_j \times CAR_{y-1} \times MP_t$	-0.602*	-0.602*	-0.487**
	(0.331)	(0.331)	(0.192)
$RiskH_j \times CAR_{y-1}$	0.00327*	0.00327*	0.00192*
	(0.00188)	(0.00188)	(0.00108)
$RiskH_j \times MP_t$	7.605*	7.604*	6.137**
	(4.173)	(4.173)	(2.415)
Branch FE	yes	yes	yes
Year-quarter FE	yes	yes	yes
Initial controls × year FE	yes	yes	yes
R^2	0.353	0.353	0.353
Observations	333,500	333,500	333,500

Notes: CAR 1 is measured by old CAR for the year before 2013, and the average value of old CAR before 2013 for the year after 2013. CAR 2 is measured by old CAR for the year before 2013, and the value of old CAR in 2013 for the year after 2013. CAR 3 is measured by old CAR before 2013, and the demeaned new CAR plus the average value of old CAR before 2013 for the year after 2013. 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 interacted with the year fixed effects. The numbers in the parentheses show the 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.

of aggregate credit measured by total social financing (TSF) in China. In recent years, the People's Bank of China (PBOC) has also targeted TSF growth for macroeconomic stabilization. To examine the robustness of our baseline findings, we replace the monetary policy shock (MP_t) in the baseline model by an aggregate credit supply shock (denoted by SF_t) based on total social financing data, constructed using the same approach as in Chen et al. (2018).

TABLE D.4. Aggregate Credit Supply Shocks

$SOE_{i,j,t}$	(1) OLS	(2) Probit
$RiskH_j \times SF_t \times Post_y$	2.017***	1.367***
	(0.277)	(0.2794)
$RiskH_j \times Post_y$	0.00383**	0.0042***
	(0.00153)	(0.0015)
$RiskH_j \times SF_t$	-1.105***	-0.637***
	(0.144)	(0.120)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls $\times$ year FE	yes	yes
R^2	0.354	–
Observations	333,500	315,382

Notes: Columns (1)-(2) report the results in OLS and Probit estimations, respectively, where the monetary policy shock MP_t in the baseline model is replaced by the aggregate credit supply shock SF_t constructed from the total social financing data using the identification approach in Chen et al. (2018). The margin effects are reported for the Probit model. 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 interacted with the year fixed effects. 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.

Table D.4 report the estimation results in the case with credit supply shocks. These results are similar to those obtained from our baseline estimation. Under the post-2013 new regulations, an expansionary credit supply shock increases the share of SOE loans extended by the branches with high NPL ratios in the past, as does an expansionary money supply shock.[32]

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[32]Total social financing measures all sources of credit supply, including bank loans and shadow bank lending. China experienced a rapid expansion of shadow banking activities following the large-scale fiscal stimulus implemented during the global financial crisis period (Chen et al., 2018; Sun, 2019). Shadow bank lending can potentially mitigate the misallocation of capital between SOEs and POEs. For example, low-productivity SOEs could channel bank funds to high-productivity POEs through trusted loans or entrusted loans (Allen et al., 2019). In practice, however, these trusted or entrusted loans are very

Table D.5. IRB Coverage

$SOE_{i,j,t}$	(1) OLS	(2) OLS
$RiskH_j \times MP_t \times IRB_y$	0.639**	1.085**
	(0.305)	(0.503)
$RiskH_j \times IRB_y$	0.0101***	0.00516
	(0.00217)	(0.00335)
$RiskH_j \times MP_t$	0.0595	3.079
	(0.159)	(2.542)
$RiskH_j \times CAR_{y-1} \times MP_t$		-0.236
		(0.201)
$RiskH_j \times CAR_{y-1}$		0.00215*
		(0.00117)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls $\times$ year FE	yes	yes
R^2	0.353	0.353
Observations	333,500	333,500

Notes: We measure the IRB coverage by the IRB-covered share of loans in the entire bank. The model specification is the same as that in the baseline regression. The numbers in the parentheses show the robust standard errors. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

IRB coverage. In the baseline regressions, we use the post-2013 dummy ($Post_y$) to indicate the period under the new capital regulations that introduced the IRB approach, which increased the sensitivity of risk-weighted assets to loan risks. Here, we use an alternative indicator of the new regulatory regime. In particular, we replace the post-2013 dummy variable by the the share of IRB-covered loans in the entire bank. The qualitative results do not change, as shown in Table D.5.

---

small relative to the size of bank loans, suggesting that they are likely not very important for alleviating credit misallocations. For example, the PBOC data show that the stock of aggregate entrusted loans was about 11.4 trillion RMB at the end of 2019, which is relatively small compared to the aggregate bank loans (about 151.6 trillion RMB). Furthermore, SOEs are less efficient in financial intermediation than banks. Thus, having SOEs to re-channel bank funds to POEs likely adds to misallocation.