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Evidence from China**

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

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

ABSTRACT. We present evidence that monetary policy easing reduces bank risk-taking but lowers aggregate productivity in China after implementing the Basel III capital regulations in 2013. The new regulations tightened bank capital requirements and introduced a new risk-weighting approach to calculating the capital adequacy ratio (CAR). To meet tightened capital requirements, a bank can boost its effective CAR by raising capital or by increasing the share of lending to low-risk borrowers. Using confidential loan-level data from a large Chinese commercial bank, merged with firm-level data on a large set of manufacturing firms, we document robust evidence that a monetary policy expansion raises the share of new bank loans to state-owned enterprises (SOEs) after 2013, but not before, because SOE loans receive high credit ratings under government guarantees. Since SOEs are on average less productive than private firms, shifts in bank lending toward SOEs reduces aggregate productivity. We construct a two-sector general equilibrium model with bank portfolio choices and show that, under calibrated parameters, an expansionary monetary policy shock raises the share of bank lending to SOEs, leading to persistent declines in total factor productivity that partially offset the expansionary effects of monetary policy.

I. INTRODUCTION

In response to the 2008-09 Global Financial Crisis and the more recent COVID-19 pandemic, central banks around the world have aggressively eased monetary policy. While these policy responses help alleviate the pains of recessions, they may also cause concerns about financial stability. For instance, if the risk-free interest rate stays persistently low,

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it might fuel asset price booms, leading to excessive leverage and risk taking by financial institutions (Stein, 2013; Bernanke, 2020). This concern raises the important question: Should the monetary policy framework incorporate financial stability considerations?

To address these important policy issues requires a better understanding of the link between monetary policy and financial institutions' risk-taking (Adrian and Shin, 2010; Borio and Zhu, 2012). In theory, the link can be ambiguous. 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 liability 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 the expected returns. Risk-taking also depends on a bank's leverage (Dell'Ariccia et al., 2014). Under limited liability, a more leveraged bank (i.e., a bank with lower capitalization) has a greater incentive for risk-taking when it faces an increase in funding costs. 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 this paper, we examine the empirical link between monetary policy and bank risk-taking using Chinese data. 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. A significant recent change in banking regulations in China was the implementation of Basel III capital regulations. 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%), and introduced a new Internal Ratings Based (IRB) approach to calculating risk-weighted assets based on the credit risks of loans.¹

To study how the regulatory policy change has affected the response of bank risk-taking to monetary policy shocks, we use confidential loan-level data from one of the "Big Five" commercial banks in China, from which we obtained detailed information about each individual loan, including information such as the quantity, the price, and the credit rating. To obtain firm-level controls in our empirical specification, we merge the

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

loan-level data with the firm-level data from China’s Annual Survey of Industrial Firms (ASIF) maintained by the National Bureau of Statistics (NBS) of China. The ASIF contains information about 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). We identify the effects of monetary policy shocks on bank risk-taking by exploiting the cross-sectional differences in lending behaviors of those bank branches with high risk exposures (measured by the share of non-performing loans) before the change in capital regulations in 2013 relative to those with low risk exposures.

We find that, after the tightening of capital requirements in 2013, a monetary policy expansion induces bank branches with high risk exposures in the past to increase the share of lending to SOE firms, which are perceived as *ex ante* low-risk borrowers.² The estimated declines in bank risk-taking following a monetary policy expansion are both statistically significant and economically important. Our baseline estimation suggests that a one standard deviation increase in M2 growth shock raises the probability of SOE lending by 6.8% after the new regulations were put in place in 2013.

When we further control for the level of capitalization in our regression, we estimate that the same monetary policy shock raises the probability of SOE lending by up to 27%, about four times as large as that obtained in the baseline estimation.³ This result suggests that the declines in bank risk-taking following monetary policy expansion in the post-2013 periods were primarily driven by changes in risk weighting, not changes in capitalization. A bank can meet tightened capital requirements by reducing the level of

²As 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.

³In 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.

risk-weighted assets; and under the new risk-weighting approach (i.e., the IRB approach), 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.

The risk-weighting mechanism that is present in the micro-level has important implications for the transmission of monetary policy to the macroeconomy. Our finding that monetary policy easing reduces bank risk-taking under tightened capital regulations should alleviate financial-stability concerns associated with expansionary monetary policy. However, banks reduce risk-taking by raising 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., 2015a). Increased lending to SOEs can exacerbate the over-investment problem, further reducing allocative efficiency (Liu et al., 2020). Using provincial-level data, we document evidence that a positive monetary policy shock significantly reduces TFP after the new capital regulations were implemented, but not before. Although SOE loans receive *de jure* high credit ratings and are considered *ex ante* low-risk loans (reflecting 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.

To further understand the aggregate implications of capital regulations for the relation between bank risk-taking and monetary policy, we construct a two-sector quantitative general equilibrium model featuring bank portfolio choices. In line with the Basel III regulations, the risk weights on bank assets used for calculating the effective CAR in our model depend on the share of loans to SOEs, since SOE loans have lower risks and lower expected returns than private-firm loans. We calibrate the model to match Chinese data, and in particular, to moments in our firm- and loan-level data.

Consistent with our empirical evidence, the model predicts that an expansionary monetary policy shock raises bank leverage and the share of SOE lending. Since SOE loans have lower risks, raising the share of SOE lending reduces loan defaults and the bank bailout costs. However, since SOEs are less productive than private firms (i.e., POEs), raising SOE lending also leads to a persistent decline in total factor productivity (TFP). To examine the importance of the risk-weighting mechanism, we compare our baseline model's impulse responses to a monetary policy shock with a counterfactual, in which the share of SOE loans is held fixed at the steady state level. We find that allowing banks to adjust the risk weights (i.e., the share of SOE lending) significantly amplifies

the responses of bank leverage, although it also reduces TFP, partly dampening the expansionary effects of monetary policy.

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 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.

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. Without explicitly controlling for capitalization, our baseline estimation suggests that an expansionary monetary policy shock leads to a sizable reduction in loan risk during the post-2013 periods. However, when we control for the level of capitalization, the reduction in risk-taking following a positive monetary policy shock becomes four times as large. This finding suggests that the observed changes in the risk-taking channel of monetary policy were primarily driven by adjustments in risk weighting, not by capitalization.

The risk-weighting channel has importance implications for capital allocations and productivity in the macroeconomy. Since SOEs are less productive than private firms,

increased lending to SOEs reduces aggregate productivity. We find this reallocation effect of monetary policy quantitatively important, both in the provincial-level data and in our general equilibrium model. Thus, our paper also contributes to the literature that studies the reallocation channel in the presence of credit market distortions. Consistent with our findings, several empirical studies have 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 disproportionately favored SOEs despite their lower average product of capital.⁴

We contribute to the literature on the reallocation effects of macroeconomic policies by both documenting the micro evidence of the risk-taking channel and by linking the micro evidence to macro implications of monetary policy. We build a quantitative general equilibrium model that incorporates bank portfolio choices, CAR constraints, and risk-weighting of bank assets into a standard New Keynesian DSGE framework. We show that these banking frictions give rise to a new source of tradeoff facing monetary policy. An expansionary monetary policy shock increases bank leverage and stimulates macroeconomic activity. However, under the CAR constraints, banks respond to the increase in leverage by increasing the share of SOE lending, which reduces the risk weights on their assets. The increase in SOE lending lowers aggregate productivity, partly offsetting the initial stimulus effects of monetary policy.

III. A SIMPLE MODEL OF BANK RISK-TAKING

We present a static, partial equilibrium model to illustrate how bank risk-taking responds to monetary policy shocks and how capital requirements affect the responses.

The economy has a competitive banking sector, with a continuum, risk-neutral, and identical banks. The representative bank is endowed with net worth of e units of consumption goods. The 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

⁴A partial list of the recent studies that highlights the misallocation effects of macroeconomic policies includes Song et al. (2011), Reis (2013), Chang et al. (2015a), Bleck and Liu (2018), Chang et al. (2019), Liu et al. (2019), and Liu et al. (2020).

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

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

where $\phi_1, \phi_2 > 0$ and $\sigma > 0$. This parameterization implies that the lower bound $\underline{R}(\sigma)$ and the upper bound $\bar{R}(\sigma)$ of the uniform distribution are respectively given by

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

The cumulative density function is then given by

$$\mathbf{F}(R) = \frac{R - \underline{R}(\sigma)}{\bar{R}(\sigma) - \underline{R}(\sigma)} = \frac{R - \underline{R}(\sigma)}{\sigma}. \quad (3)$$

Thus, under given values of ϕ_1 and ϕ_2 , the project's type is indexed by its riskiness σ .

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

We assume that the bank has limited liability. The bank takes the deposit interest rate r and the stochastic project return R as given, and solve the profit maximizing problem

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

subject to the flow-of-funds constraint

$$k = e + d, \quad (5)$$

and a capital adequacy constraint (or equivalently, a leverage constraint). Specifically, the bank needs to maintain a minimum capital adequacy ratio (CAR), denoted by $\tilde{\psi}$. Consistent with the Basel III regulations, the bank's CAR is measured by the ratio of bank capital e to the risk-weighted assets $\xi(\sigma)k$, where k is amount of physical assets and $\xi(\sigma)$ denotes the risk weight. Specifically, the bank faces the CAR constraint

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

The CAR constraint in Eq. 6 can also be interpreted as a leverage constraint. Denote by $\lambda = \frac{k}{e}$ the leverage. Then we can rewrite the CAR constraint as

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

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

We parameterize the risk-weighting function such that $\xi(\sigma) = \mu\sigma^\rho$, where $\mu > 0$ and $\rho \in (0, 1)$. Under limited liability, there exist a break-even level of project return $R^*(\sigma; \psi)$ such that the bank remains solvent if and only if the realized return $R \geq R^*(\sigma; \psi)$. It is straightforward to show that the break-even level of project return is given by

$$R^*(\sigma; \psi) = r(1 - \psi\sigma^\rho), \quad (8)$$

where $\psi \equiv \tilde{\psi}\mu$.

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

$$\begin{aligned} V &= \max_{\{\sigma\}} \frac{e}{\psi\sigma^\rho} \int_{R^*(\sigma; \psi)}^{\bar{R}(\sigma)} [R - R^*(\sigma; \psi)] d\mathbf{F}(R) \\ &= \max_{\{\sigma\}} \frac{e}{2\psi\sigma^{\rho+1}} [\bar{R}(\sigma) - R^*(\sigma; \psi)]^2, \end{aligned} \quad (9)$$

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

To ensure that $R^*(\sigma; \psi) > \underline{R}(\sigma)$, a sufficient condition is that

$$r(1 - \psi\sigma^\rho) > r(1 - \psi\bar{\sigma}^\rho) > \underline{R}^{\max}, \quad (10)$$

where, from the definition of $\underline{R}(\sigma)$ in Eq. (2), $\bar{\sigma} \equiv \arg \max_{\sigma} \underline{R}(\sigma) = \frac{\phi_1 - \frac{1}{2}}{2\phi_2}$ and $\underline{R}^{\max} \equiv \underline{R}(\bar{\sigma}) = \frac{(\phi_1 - \frac{1}{2})^2}{4\phi_2}$. Simplifying this condition to obtain

$$\psi\bar{\sigma}^\rho < 1 - \frac{(\phi_1 - \frac{1}{2})^2}{4\phi_2 r}. \quad (11)$$

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

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

$$\frac{1 + \rho}{2\sigma} [\bar{R}(\sigma) - R^*(\sigma; \psi)] = \frac{\partial [\bar{R}(\sigma) - R^*(\sigma; \psi)]}{\partial \sigma}. \quad (12)$$

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 $R^*(\sigma; \psi)$. That is, $\frac{\partial [\bar{R}(\sigma) - R^*(\sigma; \psi)]}{\partial \sigma} > 0$. 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.

The bank's optimizing decisions under CAR constraints imply that tightening the CAR constraint by either raising the required level of capitalization (ψ) or increasing the elasticity of risk-weighting (ρ) would lead to less risk-taking by the bank. This is because tightening the CAR constraint reduces the bank's leverage ratio, inhibiting its risk-taking ability. This result is formally stated in the proposition below.

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

$$\frac{\partial \sigma}{\partial \psi} < 0, \quad \frac{\partial \sigma}{\partial \rho} < 0 \quad (13)$$

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

Proof. See Appendix A.1. □

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 $R^*(\sigma; \psi) = r(1 - \psi\sigma^\rho)$ 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 next proposition.⁵

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,

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

Proof. See Appendix A.2. □

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

⁵In 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 strengthen the relation between risk-taking and monetary policy that we establish in Proposition 2.

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). 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. These results are formally stated in the proposition below.

Proposition 3. 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 elasticity of risk-weighting measured by ρ . In particular, we have

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

Proof. See Appendix A.3. □

IV. EMPIRICAL ANALYSIS

The simple theoretical model in Section III has three key predictions. First, tightening CAR regulations reduces bank risk-taking. Second, under given CAR regulations, an expansionary monetary policy shock increases bank leverage and reduces risk-taking. Third, changes in CAR regulations affect the sensitivity of bank risk-taking to monetary policy shocks. In particular, at a given level of required capitalization, increasing the sensitivity of the risk weights on bank assets to changes in portfolio risks amplifies the reduction in risk-taking following a monetary policy expansion. These theoretical predictions are supported by empirical evidence.

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). 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.⁶ 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., 2015a). Under such preferential 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 an OLS specification and an ordered Probit model. In each case, we obtained a positive

⁶ 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).

TABLE 2. Credit Ratings and SOE Loans

Credit Rating	(1) OLS	(2) Ordered Probit	(3) Ordered Probit	(4) Ordered Probit
SOE loan	2.081*** (0.025)	0.884*** (0.008)	0.796*** (0.009)	0.868*** (0.011)
Branch FE	yes	no	no	yes
Year-quarter FE	yes	no	yes	yes
Initial controls \times year FE	yes	no	yes	yes
R ²	0.236	–	–	–
Observations	264,213	264,213	264,213	264,213

Notes: Column (1) reports the results in OLS estimation. Columns (2)-(4) report results in ordered Probit estimation. Initial Controls contain the firm’s characteristics such as firm size, ROA, age, and leverage in the year of 2007. 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 $p < 0.1$.

correlation between credit ratings and SOE shares, and the correlation is significant at the 99% confidence level.

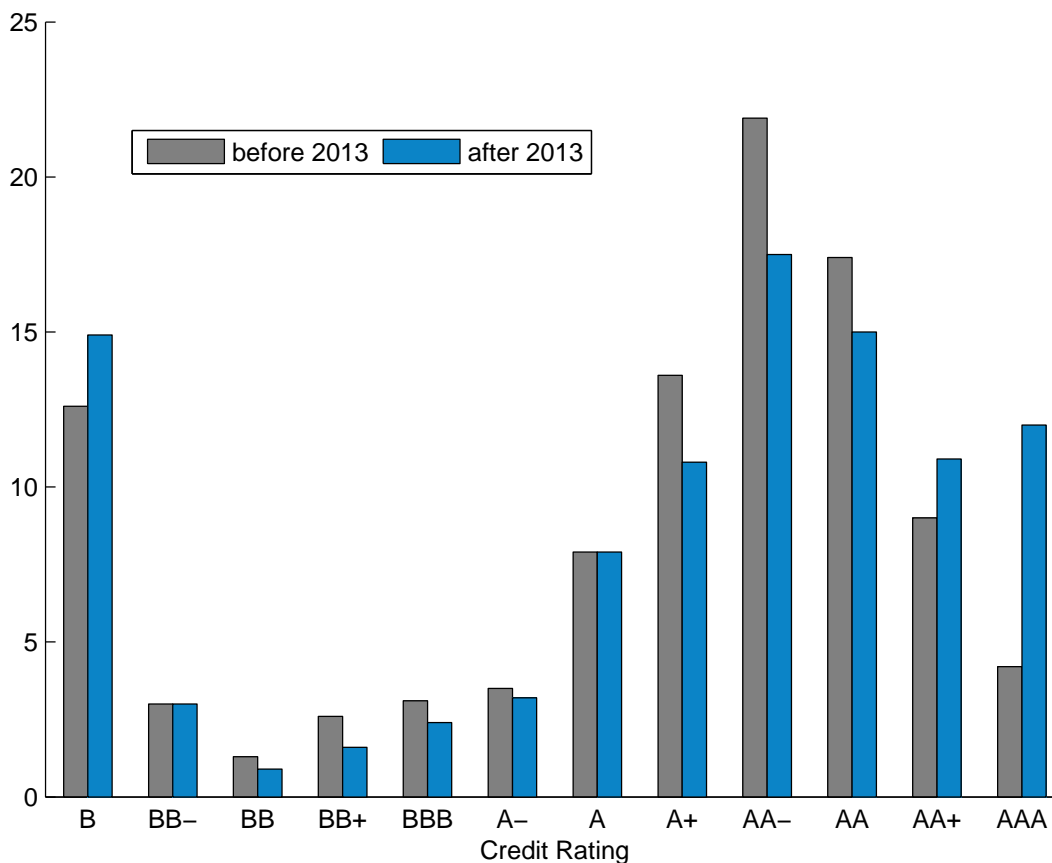
IV.1.3. *Changes in banking regulations and bank risk-taking.* The Basel III regulations implemented in 2013 raised the minimum CAR from 8% to 10.5%. It has also introduced the IRB approach for weighting bank asset risks based on loan default probabilities and default exposures.⁷

According to our theory in Section III, tightening CAR regulations should reduce bank risk-taking. Consistent with this prediction, Figure 1 shows that the distribution of credit ratings of banks loans has skewed toward high-quality loans (based on credit ratings) after implementing Basel III regulations in 2013. In particular, the share of AAA-rated loans increased sharply from 4% to 12% since 2013.

Figure 2 shows the time series of the share of high-quality loans (i.e., those loans rated AAA or AA+). The share of high-quality loans has declined steadily from 2008 to 2012. However, since the implementation of the Basel III regulations in 2013, the share of high-quality loans has increased steadily. Indeed, 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 tightened 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 after 2013. This is consistent with the time series of the share of SOE loans shown in Figure 2. The figure shows that the share of lending to SOEs has been declining before 2013, reflecting the underlying trend declines in the SOE sector

⁷The 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 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.”

FIGURE 1. Distribution of Credit Ratings



Notes: This figure reports the shares of loans with different credit ratings. The grey bars are the shares computed based on the data from 2008 to 2012. The blue bars are the shares computed based on the data from 2013 to 2017.

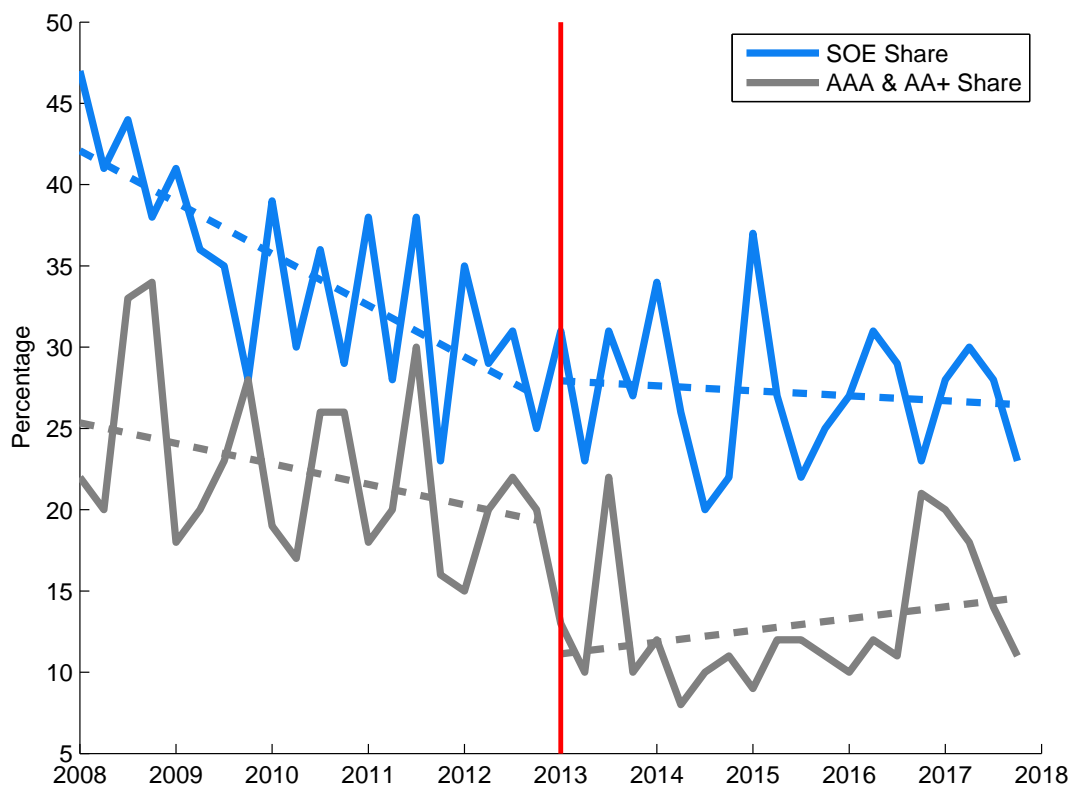
in the economy.⁸ However, since 2013, the share of SOE loans has stabilized, indicating that banks increased lending to SOEs relative to the long-term trend after the tightening of capital regulations.

IV.2. The empirical model and the estimation approach. To study how changes in capital regulations affect the responses of bank risk-taking following a monetary policy shock, we estimate the tripple-difference empirical specification

$$\begin{aligned}
 SOE_{ijt} = & \alpha \times RiskM_j \times Post_y + \beta \times RiskM_j \times Post_y \times MP_t \\
 & + \gamma \times RiskM_j \times MP_t + \theta \times X_i \times \mu_y + \eta_j + \mu_t + \epsilon_{ijt}.
 \end{aligned} \tag{16}$$

⁸Chang et al. (2015a) 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.

FIGURE 2. The Share of SOE Loans



Notes: The blue line is the share of SOE loans to the total amount of loans. The grey line is the share of high quality loan (with credit rating AA+ and AAA) to the total loans. The unit is percentage point. 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 break for the share of SOE loans around 2013.

In this specification, the dependent variable SOE_{ijt} is a dummy variable that take 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. The variable $Post_y$ is a dummy variable that is equal to one if the year is 2013 or after, and zero otherwise. It indicates the post-2013 periods with tightened capital requirements.

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.⁹ Empirical evidence suggests that experiences of financial losses in the past make an investor less willing to take risks (Andersen et al., 2019). Thus, those bank branches with a higher average share of non-performing loans (NPL) in the past (before 2013) are more

⁹According 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.

likely to face higher risk weights for their assets, and therefore, they are more sensitive to the tightening of capital regulations. Such “risk memories” help us to identify the causal effects of changes in risk-weighting regulations on branch-level lending decisions. Thus, we use those bank branches with high NPL ratios in the past as the treatment group, and the rest branches as the control group.¹⁰ In our empirical specification, the variable $RiskM_j$ captures this risk memory effect for the city-level branch j . It is a dummy variable that is equal to one if the average NPL ratio of j in the periods 2008-2012 is above the median, and zero otherwise.

The variable MP_t in Eq. (16) measures exogenous monetary policy shocks. It 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). The variable X_i 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 initial conditions X_i with the year fixed effect μ_y .¹¹ 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.¹²

The first interaction term $RiskM_j \times Post_y$ characterizes the effect of changes in bank regulations on the bank’s risk-taking behaviors. From our theory (Proposition 1), we should expect the coefficient α to be positive, such that tightening CAR regulations increases the share of new loans to safe borrowers (SOEs); and this effect should be stronger for those branches with a higher share of non-performing loans in the past. The second interaction term $RiskM_j \times Post_y \times MP_t$ captures the effect of the changes in bank regulations on the transmission of monetary policy shock. A monetary policy expansion

¹⁰ We have estimated the parallel trend for the difference-in-difference setting. We find no significant differences in the probability of lending to SOEs between branches with high NPL ratios and those with low NPL ratios before the regulation change in 2013, confirming that the treatment variable is exogenous to the regulatory policy change.

¹¹ One advantage of this approach is that the interaction term is exogenous to changes in banking regulations after 2013.

¹² In the empirical specification (16), the effects of the linear term $RiskM_j$ 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.

increases the credit supply and therefore boosts the bank's leverage. After tightening capital regulations, bank branches would want to reduce the overall loan risks as their balance sheets expand, and the reduction in risk-taking should be more pronounced for those branches with higher NPL ratios in the past. Thus, we should expect the coefficient β to be positive. The difference between β and α measures the net effect of monetary policy expansions after the tightening of capital regulations. The parameter γ 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 would raise bank leverage and reduce risk taking (see Proposition 2). However, before the introduction of the IRB 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 .

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. (16). Table 3 reports the estimation results. Column (1) shows the OLS result. The estimated values of both α and β are positive and statistically significant at the 99% confidence level.¹³ These empirical results are in line with our theory's predictions. The positive value of α suggests that, after the tightening of the CAR in 2013, bank branches (especially those with risky balance sheets in the past) reduce their risk exposure by raising the share of lending to SOEs, since SOE loans have high credit ratings and are considered safe. The positive value of β implies that an expansionary monetary policy shock increases bank lending to SOEs after the tightening of the CAR, but not before. Indeed, monetary policy shocks did not affect bank risk-taking behaviors by itself, as evidenced by the insignificant estimate of the parameter γ . We obtain similar results when we estimate a Probit model instead of an OLS model (see Column (2) of the table).

The point estimate of $\beta = 0.586$ implies that, for those bank branches with a high NPL ratio in the past, a one standard deviation increase in monetary policy shock (0.7%) would raise the probability of lending to SOEs by $0.586 \times 0.7\% = 0.41\%$. Since the sample average of the number of loans extended to SOEs is 6%, a one standard deviation increase in the monetary policy shock would thus raise the probability of SOE lending by $0.41/6 = 6.8\%$. In this sense, our estimated effects of monetary policy shocks on bank

¹³We 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 Appendix C.

TABLE 3. Effects of Regulations on Bank's Risk-Taking

	(1)	(2)	(3)	(4)
$SOE_{i,j,t}$	OLS	Probit	OLS	Probit
$RiskM_j \times Post_y$	0.0060*** (0.0016)	0.0054*** (0.0016)	0.0021 (0.0022)	0.0017 (0.0024)
$RiskM_j \times MP_t \times Post_y$	0.5863*** (0.2264)	0.5314** (0.2066)	2.3049*** (0.4262)	1.9802*** (0.4643)
$RiskM_j \times MP_t$	-0.0157 (0.1821)	0.0350 (0.1399)	10.0256*** (2.2376)	8.2457*** (2.3875)
$RiskM_j \times MP_t \times CAR_t$			-0.8146*** (0.1792)	-0.6697*** (0.1943)
$RiskM_j \times CAR_t$			0.0011 (0.0011)	0.0012 (0.0011)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial controls \times year FE	yes	yes	yes	yes
R ² /Pseudo R ²	0.251	0.333	0.251	0.292
Observations	365,684	347,129	365,684	347,129

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. 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.

risk-taking under tightened 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 risk weighting

of bank assets can also affect risk-taking conditional on monetary policy shocks (Proposition 3).

The implementation of Basel III in 2013 raised the required CAR from 8% to 10.5%.¹⁴ It also introduced the new IRB approach for calculating risk-weighted assets, increasing the sensitivity of risk weighting to credit risks. To disentangle the effects of changes in risk weighting from that of changes in capitalization on the bank's risk-taking behaviors, we augment our baseline empirical specification (16) by including two additional controls that capture the effects of capitalization—the effective quarterly CAR of the bank (CAR_t) and the interactions between the effective CAR and monetary policy shocks ($MP_t \times CAR_t$)—both interacted with the $RiskM_j$ term.¹⁵ This empirical specification allows us to isolate the effects of changes in risk weighting on the risk-taking channel of monetary policy shocks, controlling for the effects of changes in bank capitalization.

Table 3 reports the estimation results (Columns (3) and (4)). 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. Column (3) shows the OLS results when we add controls for the level of capitalization (measured by the effective CAR) in the baseline regression. The estimated coefficient on $RiskM_j \times MP_t \times CAR_t$ is 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 $RiskM_j \times MP_t \times POST_y$ remains significantly positive, with a magnitude about 4 times as large as that in baseline regression (2.305 vs. 0.586). The point estimate (2.305) implies that a one standard deviation monetary policy shock would increase the probability of SOE lending by about 27%. We obtained similar results when we estimate the Probit model (see Column (4)).¹⁶ These findings suggest, consistent with our theory, that the reductions in bank risk-taking following a monetary policy expansion were primarily driven by changes in risk weighting in the post-2013 periods.

¹⁴The minimum CAR for systemically important banks was raised to 11.5%.

¹⁵The 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.

¹⁶We 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.

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

IV.4.1. *Lead-lag Effects.* It is possible that changes in the banking regulation may have changed the bank risk-taking behaviors before its actual implementation in 2013 because of some anticipation effects. It is also possible that bank lending may respond to changes in regulations with some lags. To examine these potential lead-lag effects, we estimate the empirical model

$$SOE_{i,j,t} = \alpha \times RiskM_j \times Post_y + \sum_{\tau=2011}^{2014} \beta_{\tau} \times RiskM_j \times \delta_{\tau} \times MP_t + \gamma \times RiskM_j \times MP_t + \theta \times X_i \times \mu_y + \eta_j + \mu_t + \epsilon_{i,j,t}, \quad (17)$$

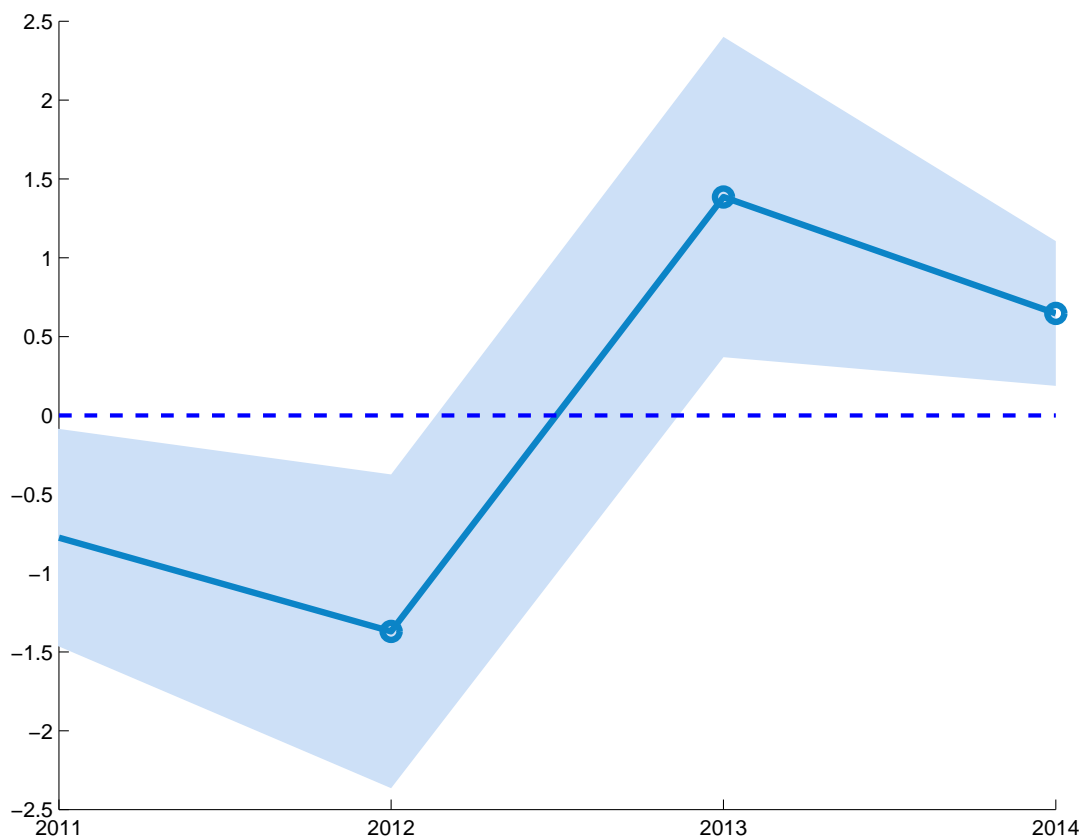
where δ_{τ} denotes a year dummy, which is equal to one in year τ , and zero otherwise. The other variables have the same definitions as in the baseline model specified in Eq. (16). The parameter β_{τ} measures the lead or lag effects of the regulation changes on the transmission of monetary policy shock in the period of $\tau - 2013$ years before or after the effective year 2013.

Figure 3 shows the point estimates of β_{τ} along with the 95% confidence bands. The estimated value of β_{τ} is significantly negative in 2011 and 2012, before the Basel III implementation. The negative values of β_{τ} imply that the branches with high NPL ratios and thus large risk exposures in the past reduced the share of lending to SOEs in response to a positive monetary policy shock, suggesting more risk-taking. However, starting in 2013 when the new regulations were implemented, the estimated β_{τ} turns significantly positive, implying a reduction in risk-taking for those branches with high NPL ratios following a positive monetary policy shock. Thus, the change in banking regulations in 2013 has led to systematically different risk-taking behaviors in bank lending following a monetary policy shock.

IV.4.2. *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-estimated our baseline model using these alternative SOE definitions. Table 4 shows that the main results obtained in our baseline regressions are not sensitive to these alternative SOE definitions.

IV.4.3. *Aggregate credit supply shocks.* In recent years, the People's Bank of China (PBC) has also targeted the growth rate of total social financing, which measures the

FIGURE 3. The Lead-lag Effects of Regulation



Notes: This figure reports the estimation of parameters β_τ , for $\tau = \{2011, 2012, 2013, 2014\}$. The shadow area indicates the 95% confidence interval.

aggregate credit supply in China. We construct an exogenous credit supply shock, SF_t , from the total social financing data by applying the same approach developed in Chen et al. (2018). We then replace the monetary policy variable MP_t in the baseline estimation with the credit supply shock that we obtained.

Table 5 report the estimation results in the case with credit supply shocks. These results are similar to those obtained from our baseline estimation, suggesting that 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.

IV.4.4. *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 has liberalized controls over bank lending rates. Subsequently, in 2015, the

TABLE 4. Robustness: Alternative Definitions of SOEs

$SOE_{i,j,t}$	(1)	(2)	(3)	(4)
	SOE 1		SOE 2	
	OLS	Probit	OLS	Probit
$RiskM_j \times Post_y$	0.0009 (0.0012)	0.0002 (0.0014)	0.0061*** (0.0011)	0.004** (0.0014)
$RiskM_j \times MP_t \times Post_y$	0.398** (0.168)	0.361* (0.191)	0.418*** (0.155)	0.588*** (0.184)
$RiskM_j \times MP_t$	-0.209 (0.137)	-0.223* (0.121)	-0.140 (0.127)	-0.135 (0.121)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial control \times year FE	yes	yes	yes	yes
R ²	0.210	–	0.191	–
Observations	320,311	244,259	323,511	222,733

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.

PBOC also widened the range of the deposit rates that banks can offer. These interest-rate liberalization policies might present some confounding factors for identifying the impact of the post-2013 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 $RiskM_j \times LoanRateGap_t$ and $RiskM_j \times MP_t \times LoanRateGap_t$ as additional independent variables in our regression. Here, the variable

TABLE 5. Robustness: Alternative measure of monetary policy shocks

	(1)	(2)
$SOE_{i,j,t}$	OLS	Probit
$RiskM_j \times Post_y$	0.0044*** (0.0016)	0.0043** (0.0017)
$RiskM_j \times SF_t \times Post_y$	1.673*** (0.290)	1.509*** (0.309)
$RiskM_j \times SF_t$	-0.660*** (0.152)	-0.491*** (0.126)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls \times year FE	yes	yes
R ²	0.251	–
Observations	365,684	347,129

Notes: Columns (1)-(2) report the results in OLS and Probit estimations, respectively, where the monetary policy shock MP_t is replaced with the 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.

$LoanRateGap_t$ 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 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 6 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 lower 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 marginally significant at the 90% level.

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. As in the baseline model, in the post-2013 period with tightened capital regulations, the branches with high risk exposures in the past increase their lending to SOEs. These bank branches will increase SOE lending even more following an expansionary monetary policy shock in the post-2013 periods relative to before. 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, and they are not driven by other reforms such as interest-rate liberalization.

IV.4.5. *Effects of deleveraging policy: A placebo test.* The Chinese government responded to the 2008-09 global financial crisis by implementing a large-scale fiscal stimulus (equivalent to about 12% of GDP). The fiscal stimulus helped cushion the downturn during the crisis 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 high 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 16, replacing the variable $Post_y$ in the baseline model with $DeLev_y$. Table 7 shows the estimation results. Unlike the Basel III implementation, the deleveraging policy had no impact on the bank’s risk-taking behaviors conditional on monetary policy shocks.

IV.4.6. *Additional controls.* Our baseline regression includes controls for branch fixed effects, year-quarter fixed effects, and the interaction 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

TABLE 6. Controlling for the impact of interest-rate liberalization

	(1)	(2)
$SOE_{i,j,t}$	OLS	Probit
$RiskM_j \times Post_y$	0.0066*** (0.0016)	0.0062*** (0.0016)
$RiskM_j \times MP_t \times Post_y$	0.7754*** (0.2357)	0.7219*** (0.2195)
$RiskM_j \times MP_t$	0.3729 (0.3236)	0.4030 (0.2944)
$RiskM_j \times MP_t \times LoanRateGap_t$	-4.5406* (2.8828)	-4.6103 (2.9999)
$RiskM_j \times LoanRateGap_t$	0.0565*** (0.0199)	0.0713*** (0.0205)
Branch FE	yes	yes
Year-quarter FE	yes	yes
Initial controls \times year FE	yes	yes
R ² / Pseudo R ²	0.231	0.293
Observations	365,684	347,129

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

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.¹⁷

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

¹⁷The bank 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 7. Robustness: Deleveraging Policy

	(1)	(2)	(3)	(4)
$SOE_{i,j,t}$	OLS	OLS	Probit	Probit
$RiskM_j \times Delev_y$	-0.0003 (0.0018)	-0.0012 (0.0023)	-0.0014 (0.0020)	-0.0023 (0.0026)
$RiskM_j \times MP_t \times Delev_y$		-0.558 (0.589)		-0.504 (0.603)
$RiskM_j \times MP_t$		0.149 (0.102)		0.153 (0.981)
Branch FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Initial control \times year FE	yes	yes	yes	yes
R ²	0.251	0.251	–	–
Observations	365,684	365,684	347,129	347,129

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.

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 $RiskM_j$ can be potentially endogenous.

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

Table 8 shows the regression results with these additional controls (one at a time). Our main findings in the baseline estimation remain robust: the regulation changes induce the bank to issue more loans to SOEs in response to a positive monetary policy shock.

TABLE 8. Robustness: Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
$SOE_{i,j,t}$	OLS	OLS	OLS	Probit	Probit	Probit
$RiskM_j \times Post_y$	0.0061*** (0.0016)	0.0046*** (0.0016)	0.0027* (0.0015)	0.0056*** (0.0016)	0.0032** (0.0016)	0.0039*** (0.0015)
$RiskM_j \times MP_t \times Post_y$	0.582** (0.226)	0.572** (0.224)	0.677*** (0.208)	0.553*** (0.207)	0.509** (0.206)	0.640*** (0.199)
$RiskM_j \times MP_t$	-0.0051 (0.182)	-0.0158 (0.180)	-0.171 (0.165)	0.0318 (0.141)	0.0405 (0.145)	-0.144 (0.135)
$InitProfit_j \times \text{year FE}$	yes	yes	yes	yes	yes	yes
$InitSOE_j \times \text{year FE}$	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	0.252	0.260	0.403	–	–	–
Observations	365,684	365,684	320,311	347,129	347,129	296,325

Notes: Columns (1)-(3) and (4)-(6) report the results in OLS and Probit estimations, respectively. The $InitProfit_j$ is measured by the net 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.

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. 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.

TABLE 9. Ex Post Performances of SOE Loans

	(1)	(2)	(3)	(4)
	NPL	NPL	Overdue	Overdue
	OLS	Probit	OLS	Probit
SOE Loan	0.0105*** (0.0015)	0.0228*** (0.0021)	0.0179*** (0.0016)	0.0318*** (0.0020)
Credit Rating	-0.0119*** (0.0002)	-0.0117*** (0.0002)	-0.0161*** (0.0002)	-0.0150*** (0.0002)
Branch FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Initial controls \times year FE	yes	yes	yes	yes
R ²	0.084	–	0.112	–
Observations	255,640	247,629	263,551	259,348

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 last status of the loan 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.

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 9 shows that, all else 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

TABLE 10. Effects of Regulation on Provincial TFP Growth Rates

	(1)	(2)
	TFP Growth	TFP Growth
$Post_y$	-0.0298*** (0.0059)	-0.0370*** (0.0061)
MP_t	2.847*** (0.988)	2.636*** (0.923)
$MP_t \times Post_y$	-9.688*** (1.197)	-8.180*** (1.150)
Controls	no	yes
Province FE	yes	yes
Observations	300	300
R ²	0.288	0.372
Number of Provinces	30	30

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 other variables (MP_t and $Post_y$) have the same definitions as those in the baseline estimation. In both columns (1) and (2), we include controls for the province fixed effects. In Column (2), we add additional controls for a set of provincial characteristics, including FDI/GDP, (imports+exports)/GDP, and aged population share. All the provincial data are obtained from the WIND database. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

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 provincial level data based on the approach

in Brandt et al. (2013). Appendix D provides the details of our calculations of the provincial TFP.

Table 10 shows that estimation results in the specification in which the provincial TFP growth rates depend on the post-2013 dummy $Post_y$, the monetary policy shock MP_t , and the interactions between the two. In both columns, we control for province fixed effects. In Column (2), we include additional controls for provincial characteristics such as the ratio of local FDI to local GDP, the province's openness to trade, and population ages. The estimation shows that the implementation of the Basel III regulations was associated with a significant decline in provincial TFP growth. Furthermore, an expansionary monetary policy shock reduced provincial TFP growth after 2013, but not before. These effects are statistically significant and economically important. The point estimate implies that a positive one standard deviation shock to monetary policy in the post-2013 period reduces provincial TFP growth by about 2.7 percentage points.¹⁸ Our finding here suggests that the tightened bank capital regulations, by raising the share of bank lending to SOEs in response to expansionary monetary policy shocks, have contributions to aggregate productivity slowdown.

V. A TWO-SECTOR GENERAL EQUILIBRIUM MODEL WITH BANK RISK-TAKING

We have presented micro evidence that the tightened capital regulations in China have reduced bank risk-taking, both on average and conditional on an expansionary monetary policy shock. Our evidence suggests that banks reduce loan risks by raising the share of lending to SOEs, lowering aggregate productivity. Is this risk-taking channel of monetary policy important in the aggregate economy?

To answer this question requires a general equilibrium framework that allows us to examine how changes in banking regulations affect the portfolio choices in bank lending decisions, and how bank lending affects capital allocations among firms in different sectors, particularly following a monetary policy shock. We now present such a two-sector dynamic general equilibrium model.

V.1. The dynamic model. The economy features a competitive banking sector, in which the representative bank takes deposits from households and lends to two types of intermediate goods producers: SOEs and POEs. Each firm faces idiosyncratic productivity shocks, such that the bank receives stochastic returns from lending. Consistent with empirical evidence, we assume that SOE projects yield lower expected returns but also

¹⁸In our sample, the standard deviation of the monetary policy shock is about 0.28% (at the annual frequency). Thus, the point estimate of -9.688 for the term $MP_t \times Post_y$ implies a reduction in TFP growth of $9.688 \times 0.28\% = 2.7\%$.

bear lower risks than POE projects. Under a CAR constraint, banks need to maintain a minimum ratio of net worth to risk-weighted assets, where the risk weights depend on the share of safe loans (i.e., SOE lending). The household consumes a final good produced using intermediate goods as inputs. Intermediate goods are produced using labor and capital as inputs. Retail prices are sticky, such that monetary policy has real effects. In light of the empirical study of Chen et al. (2018), we assume that the central bank follows a money supply rule, under which the money growth rate is adjusted to stabilize deviations of inflation and output growth from their respective targets.

V.1.1. *The banking sector.* The banking sector is populated by a continuum of banks with measure one. To simplify the analysis, we follow Coimbra and Rey (2017) and assume banks live for two periods. In the first period, the representative bank makes loan (i.e., investment) decisions; in the second period, the bank obtains payoffs from the loans. Each bank entering the market in period t is endowed with equity e_t . It takes deposits d_t from a large mutual fund (on behalf of the households) at the competitive real deposit rate R_t^d . The equities and deposits are both measured in final good units. The total funds available to the bank is therefore $e_t + d_t$.

The bank lends out its available funds to intermediate-good producers. The firms use the loans to finance purchases of capital k_{t+1} from capital producers at the competitive price Q_t . The value of loans (i.e., the bank asset value) is thus $Q_t k_{t+1}$. The bank faces the flow-of-funds constraint

$$Q_t k_{t+1} = e_t + d_t. \quad (18)$$

The bank chooses to allocate a fraction ω_t of the loans $Q_t k_{t+1}$ to SOE projects and remaining $1 - \omega_t$ fraction to POE projects. Firms in sector $j \in \{s, p\}$ face the idiosyncratic productivity \tilde{z}_j , where s and p denote the SOE sector and POE sector, respectively. We assume that \tilde{z}_j follows the log-normal distribution $\mathbf{F}_j(\tilde{z}_j)$, with a mean of $\tilde{\mu}_j$ and a standard deviation of $\tilde{\sigma}_j$. The SOE projects yield lower returns and bear lower risks than the POE projects. That is, $\tilde{\mu}_s < \tilde{\mu}_p$ and $\tilde{\sigma}_s^2 < \tilde{\sigma}_p^2$.

In period $t + 1$, a firm of type $j \in \{s, p\}$ produces a homogeneous intermediate good using the capital k_{jt+1} and labor l_{jt+1} as inputs, with the Cobb-Douglas production function

$$y_{jt+1} = (\tilde{z}_j k_{jt+1})^\alpha l_{jt+1}^{1-\alpha}, \quad (19)$$

where $\alpha \in (0, 1)$ is the output elasticity of effective capital.

Profit maximizing implies that the capital return of a type j project is given by $r_{t+1} \tilde{z}_j k_{jt+1}$

$$r_{t+1} \tilde{z}_j k_{jt+1} = \max_{l_{jt+1}} p_{t+1}^m (\tilde{z}_j k_{jt+1})^\alpha l_{jt+1}^{1-\alpha} - W_{t+1} l_{jt+1}, \quad (20)$$

where W_t debotes the real wage rate and p_t^m debotes the relative price of intermediate goods. The optimal choice of labor input implies that the marginal product of effective capital is given by

$$\tilde{z}_j k_{jt+1} r_{t+1} = \alpha \left(\frac{1 - \alpha}{W_{t+1}/p_{t+1}^m} \right)^{\frac{1-\alpha}{\alpha}}, \quad (21)$$

which depends on aggregate states only.

At the end of period $t + 1$, the firms sell the capital $(1 - \delta)k_{jt+1}$ after depreciation at the rate $\delta \in (0, 1)$, at the capital price Q_{t+1} as a part of loan repayments to the bank. Thus, the investment income from a type j project is $r_{t+1} \tilde{z}_j k_{jt+1} + (1 - \delta) Q_{t+1} k_{jt+1}$.

The investment efficiency of the bank loan portfolio is a weighted average of the two types of projects given by $z_t = \tilde{\mathbf{z}} \Omega_t$, where $\Omega_t = [\omega_t, 1 - \omega_t]'$ and $\tilde{\mathbf{z}} = [\tilde{z}_s, \tilde{z}_p]$. Denote by $f(z_t; \omega_t)$ the probability density function (PDF) of z_t , with the mean μ_{z_t} and the standard deviation σ_{z_t} . The term σ_{z_t} captures the riskiness of the bank loan portfolio, and it decreases with the share of SOE loans ω_t .¹⁹

The bank faces the CAR constraint that requires its capital adequacy ratio (denoted by ψ_t) to exceed a minimum level $\tilde{\psi}$. Under the Basel III regulations, the bank's effective CAR is measured by the ratio of its equity to its risk-weighted assets. Specifically, the CAR constraint is given by

$$\psi_t = \frac{e_t}{h(\omega_t) Q_t k_{t+1}} \geq \tilde{\psi}, \quad (22)$$

where $h(\omega_t)$ denotes a risk-weighting function. Consistent with the IRB approach implemented in China under the Basel III regulations, we assume that $h(\omega_t)$ decreases with the share of safe loans, which in our model, corresponds to the share of SOE loans (ω_t). In particular, we assume that the risk-weighting function takes the form

$$h(\omega_t) = \xi \omega_t^\chi, \quad (23)$$

where $\xi > 0$ and $\chi < 0$.

As in the static model of Section III, the CAR constraint is equivalent to the leverage constraint

$$\lambda_t \leq \frac{1}{\tilde{\psi} h(\omega_t)}, \quad (24)$$

where $\lambda_t \equiv \frac{Q_t k_{t+1}}{e_t}$ is the leverage ratio.²⁰

¹⁹Since z_t is a weighted average of two independently distributed log-normal random variables (\tilde{z}_s and \tilde{z}_p) with endogenous weights (ω_t), the distribution of z_t can be highly complex, presenting computational challenges for solving the model. To keep our analysis tractable, we follow Pratesi et al. (2006) and use a log-normal distribution to approximate $f(z_t; \omega_t)$. See Appendix E.4 for details.

²⁰Our specification of the financial constraints facing banks is different from the financial accelerator models in the literature (Bernanke et al., 1999; Gertler and Kiyotaki, 2010). In our model, changes in

The bank maximizes the profit $r_{t+1}z_t k_{t+1} + (1 - \delta) Q_{t+1} k_{t+1} - R_t^d d_t$, subject to the flow-of-funds constraint (18) and the CAR constraint (22). Under limited liability, the bank's optimizing problem can be written as

$$V_{t+1} = \max_{k_{t+1}, d_t, \omega_t} \int \max \{ r_{t+1} z_t k_{t+1} + (1 - \delta) Q_{t+1} k_{t+1} - R_t^d d_t, 0 \} f(z; \omega_t) dz, \quad (25)$$

subject to the flow-of-funds constraint (18) and the leverage constraint (24) (or equivalently, the CAR constraint (22)). Limited liability implies that there exists a cutoff level of investment efficiency, denoted by z_t^* , such that banks earn zero profit if and only if $z_t \leq z_t^*$. The cutoff point is given by

$$z_t^* \equiv \frac{R_t^d Q_t \left(1 - \frac{1}{\lambda_t}\right) - (1 - \delta) Q_{t+1}}{r_{t+1}}. \quad (26)$$

Using the flow-of-funds constraint (18) and the definition of the leverage ratio, the bank's optimization problem can be simplified to

$$V_{t+1} = \max_{\{\lambda_t, \omega_t\}} \frac{r_{t+1}}{Q_t} \lambda_t e_t \int_{z > z_t^*} (z - z_t^*) f(z; \omega_t) dz, \quad (27)$$

subject to (24).

Assuming that the leverage constraint (24) is binding. Then, the optimizing decision with respect to ω_t implies that

$$-\frac{h'(\omega_t)}{h(\omega_t)} \int_{z > z_t^*} (z - z_t^*) f(z; \omega_t) dz = - \int_{z > z_t^*} (z - z_t^*) \frac{\partial f(z; \omega_t)}{\partial \omega_t} dz + \frac{\partial z_t^*}{\partial \omega_t} \int_{z > z_t^*} f(z; \omega_t) dz, \quad (28)$$

where

$$\frac{\partial z_t^*}{\partial \omega_t} = -\tilde{\psi} h'(\omega_t) Q_t \frac{R_t^d}{r_{t+1}} > 0. \quad (29)$$

Eq. (28) shows the risk-return tradeoff of loan allocations between SOEs and POEs. The left side of Eq. (28) indicates the marginal benefit of increasing the share of SOE lending. Since SOE loans are less risky, increasing ω_t reduces the risk weight $h(\omega_t)$ on bank assets, relaxing the CAR constraint and allowing the bank to raise the leverage ratio. This helps increase the bank's investment returns. The right side of Eq. (28) shows the marginal cost of increasing the share of SOE lending. It consists of two terms. A change in the SOE loan share (ω_t) shifts the distribution of the portfolio returns, and this effect is captured by the first term on the right side of Eq. (28). An increase in ω_t reduces the expected return on the portfolio, although the overall impact on the distribution function $f(z; \omega_t)$ of the loan portfolio can be ambiguous, depending on the

bank leverage is partly driven by risk weighting of bank assets, rather than the agency problem between the lender and the borrower.

initial value of ω_t . The SOE loan share also affects the cutoff point for bankruptcy z_t^* , as reflected by the second term. An increase in ω_t reduces the risk weight $h(\omega_t)$ on bank assets, allowing the bank to increase the leverage ratio. As the balance sheet expands, the probability of bankruptcy increases (i.e., the break-even point z_t^* becomes larger).

In our model, a bank lives for two periods. At the end of the second period of its life, the bank distributes dividends V_t to the representative household. The household then transfers a fraction $\kappa \in [0, 1]$ of the dividends to new banks. A new bank's equity endowment e_t evolves according to the law of motion

$$e_t = \rho_e e_{t-1} + (1 - \rho_e) \kappa V_t, \quad (30)$$

where $\rho_e \in (0, 1)$ measures the persistence of the bank net worth e_t .

V.1.2. *The mutual funds.* There is a continuum of competitive mutual funds. The representative mutual fund takes deposits from households and provides funding for banks. In the event that a bank becomes insolvent, the mutual fund takes over the revenues. Following Bernanke et al. (1999), we assume that the bankruptcy cost is ζ fraction of the bank's gross return, i.e.,

$$\Psi_t = \zeta \int_{z < z_{t-1}^*} [r_t z + (1 - \delta) Q_t] k_t f(z; \omega_{t-1}) dz. \quad (31)$$

The mutual fund can recover the remaining $1 - \zeta$ fraction of bank's revenue. In addition, it receives deposit insurance payments from the government, such that the mutual fund does not suffer losses. Denote by G_t the deposit insurance payments. Then, we have

$$G_t = R_{t-1}^d d_{t-1} \int_{z < z_{t-1}^*} f(z; \omega_{t-1}) dz - (1 - \zeta) k_t \int_{z < z_{t-1}^*} [r_t z + (1 - \delta) Q_t] f(z; \omega_{t-1}) dz. \quad (32)$$

Under the deposit insurance, the mutual fund breaks even and the household receives the competitive deposit rate R_t^d on their savings in the mutual fund.

V.1.3. *The households.* The representative household has the utility function

$$\sum_{t=0}^{\infty} \beta^t \left[\log C_t - \tau_l \frac{L_t^{1+\eta}}{1+\eta} + \tau_m \log \frac{M_t}{P_t} \right], \quad (33)$$

where C_t denotes consumption, L_t denotes hours worked, and M_t/P_t denotes the real money balance. The parameter $\beta \in (0, 1)$ is a subjective discount factor, τ_l and τ_m measure the relative utility weights on leisure and money balances, respectively, and η is the inverse Frisch elasticity of labor supply.

The household maximizes the utility function (33), subject to the sequence of budget constraints

$$C_t + D_t + \frac{M_t}{P_t} = W_t L_t + R_{t-1}^d D_{t-1} + \frac{M_{t-1}}{P_t} + T_t, \quad (34)$$

where D_t denotes the savings at the mutual fund and T_t is the sum of dividend distributions from the banks and firms and lump-sum taxes or transfers from the government.

V.1.4. *The capital producers.* There is a continuum of competitive capital producers with measure one. The representative capital producer has access to an investment technology that can transform one unit of final consumption good into one unit of capital, subject to investment adjustment costs in the spirit of Christiano et al. (2005). The capital producer sells the capital to intermediate good producers at the relative price Q_t . The capital producer chooses investment I_t to solve the problem

$$\max \sum_{t=0}^{\infty} \beta^t \frac{\Lambda_t}{\Lambda_0} \left\{ Q_t I_t - \left[1 + \frac{\Omega}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t \right\}, \quad (35)$$

where Λ_t denotes the marginal utility of income for the household (who owns the capital producers) and the parameter Ω measures the scale of the investment adjustment costs.

The optimizing investment decisions imply that

$$Q_t = 1 + \frac{\Omega}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 + \Omega \left(\frac{I_t}{I_{t-1}} - 1 \right) \frac{I_t}{I_{t-1}} - \beta \frac{\Lambda_{t+1}}{\Lambda_t} \Omega \left(\frac{I_{t+1}}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2. \quad (36)$$

Absent adjustment costs (i.e., $\Omega = 0$), the relative price of capital (i.e., Tobin's q) would be constant at $Q_t = 1$.

V.1.5. *The retail goods producers and price-setting decisions.* There is a continuum of retailers producing differentiated retail products indexed by $i \in [0, 1]$ using the homogeneous intermediate good as the only input. One unit of retail product can be produced using one unit of intermediate good purchased from the firms (SOEs or POEs) at the competitive price P_t^m . The retailers face monopolistic competition in the product markets and perfect competition in the input markets. Each retailer takes as given the price level and the demand schedule for its product, and adjusts its own price subject to quadratic price adjustment costs in the spirit of Rotemberg (1982).

Final good Y_t is a Dixit-Stiglitz composite of retail products $Y_t(i)$ for $i \in [0, 1]$. Specifically,

$$Y_t = \left[\int_0^1 Y_t(i)^{(\epsilon-1)/\epsilon} \right]^{\epsilon/(\epsilon-1)}, \quad (37)$$

where $\epsilon > 1$ is the elasticity of substitution between differentiated products. The retail producer i faces the downward-sloping demand schedule $Y_t^d(i) = \left[\frac{P_t(i)}{P_t} \right]^{-\epsilon} Y_t$, where $Y_t^d(i)$

denotes the quantity, $P_t(i)$ the price of the retail product, and $P_t = \left[\int_0^1 P_t(i)^{1-\epsilon} di \right]^{1/(1-\epsilon)}$ is the price index.

Each retailer i sets a price for its own product. Price adjustments incur the resource cost $\frac{\Omega_p}{2} \left[\frac{P_t(i)}{\pi P_{t-1}(i)} - 1 \right]^2 Y_t$, where Ω_p measures the scale of price adjustment cost and π is the steady-state inflation rate. The retailer i chooses $P_{t+\tau}(i)$ to maximize the present value

$$\sum_{\tau=0}^{\infty} \beta^\tau \frac{\Lambda_{t+\tau}}{\Lambda_t} \left\{ \left(\frac{P_{t+\tau}(i)}{P_{t+\tau}} - p_{t+\tau}^m \right) \left(\frac{P_{t+\tau}(i)}{P_{t+\tau}} \right)^{-\epsilon} Y_{t+\tau} - \frac{\Omega_p}{2} \left[\frac{P_{t+\tau}(i)}{\pi P_{t+\tau-1}(i)} - 1 \right]^2 Y_{t+\tau} \right\}. \quad (38)$$

In a symmetric equilibrium with $P_t(i) = P_t$ for all i , the optimal pricing decision implies that

$$p_t^m = \frac{\epsilon - 1}{\epsilon} + \frac{\Omega_p}{\epsilon} \left[\left(\frac{\pi_t}{\pi} - 1 \right) \frac{\pi_t}{\pi} - \beta \frac{\Lambda_{t+1}}{\Lambda_t} \left(\frac{\pi_{t+1}}{\pi} - 1 \right) \frac{\pi_{t+1}}{\pi} \right]. \quad (39)$$

Absent price adjustment costs (i.e., $\Omega_p = 0$), the optimal retail price would be a constant markup over the marginal cost, such that the relative price of the intermediate goods is equal to the inverse of the markup (i.e., $p_t^m = \frac{\epsilon-1}{\epsilon}$).

V.1.6. *Monetary Policy.* The monetary authority adjusts the money supply growth to target inflation and output growth. In particular, we consider the money supply rule

$$g_{mt} = \gamma_m g_{mt-1} + \gamma_\pi (\hat{\pi}_{t-1} - \pi^*) + \gamma_{yt} (g_{yt-1} - g_y) + \varepsilon_{mt}, \quad (40)$$

where $g_{mt} = \frac{M_t}{M_{t-1}} - 1$ denotes the growth rate of money supply, $\hat{\pi}_{t-1} = \pi_{t-1} - 1$ denotes the lagged inflation rate, $g_{y,t-1} = \frac{Y_{t-1}}{Y_{t-2}} - 1$ denotes the lagged output growth rate, and we normalize both the inflation and growth targets to zero such that $\pi^* = 0$ and $g_y = 0$.

Chen et al. (2018) present empirical evidence that China's monetary policy follows an asymmetric, pro-growth money supply rule. In line with their evidence, we allow the policy coefficient γ_{yt} of the growth gap in the money supply rule to be time varying and state-dependent. In particular, we assume that

$$\gamma_{yt} = \begin{cases} \gamma_y^+ > 0, & \text{if } g_{y,t-1} \geq 0 \\ \gamma_y^- < 0, & \text{if } g_{y,t-1} < 0, \end{cases} \quad (41)$$

where $\gamma_y^+ > 0$, $\gamma_y^- < 0$, and $\gamma_y^+ < |\gamma_y^-|$. Under this policy rule, the money growth rate accelerates in the short-fall state with below-target output growth more aggressively than in the above-target state (i.e., $\gamma_y^+ < |\gamma_y^-|$), consistent with China's pro-growth and state-dependent money supply rule documented by Chen et al. (2018).

V.1.7. *Aggregation, market clearing, and equilibrium.* In an equilibrium, the labor market, the capital market, the loanable funds market, and final goods market all clear.

The market clearing conditions for labor and capital imply that

$$L_t = \sum_{j \in \{s,p\}} \int l_{jt} d\mathbf{F}_j(\tilde{z}_j), \quad K_t = \sum_{j \in \{s,p\}} \int k_{jt} d\mathbf{F}_j(\tilde{z}_j). \quad (42)$$

Under constant returns, we can derive the aggregate production function

$$Y_t = \tilde{K}_t^\alpha L_t^{1-\alpha}, \quad (43)$$

where \tilde{K}_t is the aggregate effective units of capital given by

$$\tilde{K}_t = \mu_{zt-1} K_t, \quad (44)$$

where $\mu_{zt} = \omega_t \tilde{\mu}_s + (1 - \omega_t) \tilde{\mu}_p$ measures the mean of the capital productivity z_t .

The aggregate capital stock follows the law of motion

$$K_{t+1} = (1 - \delta)K_t + I_t. \quad (45)$$

Loanable funds market clearing implies that

$$D_t = d_t. \quad (46)$$

Final good market clearing implies the aggregate resource constraint

$$C_t + \left[1 + \frac{\Omega}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t + \Psi_t = Y_t. \quad (47)$$

Under the government policies, an equilibrium in this economy consists of the prices and the allocations such that: (1) taking all prices as given, the allocations solve the optimizing problems for the household, the bank, and intermediate good producers in both sectors; (2) taking all prices but its own as given, the price for each retail product and the allocations solve the retailer's optimizing problems; and (3) the markets for labor, capital, loanable funds, and final good all clear.

V.2. Parameter calibration. We solve the model's steady state equilibrium and the transition dynamics following a monetary policy shock based on calibrated parameters. Table 11 shows our calibration.

A period in the model corresponds to one year. We set the subjective discount factor to $\beta = 0.96$, implying a steady-state real interest rate of 4 percent. We set the capital depreciation rate to $\delta = 0.1$. We set the capital income share to $\alpha = 0.5$, in line with the empirical evidence in Zhu (2012). Following Chang et al. (2015b), we set the scale of price adjustment costs to $\Omega_p = 60$ and the elasticity of substitution between differentiated retail products to $\epsilon = 11$. We set the investment adjustment cost parameter to $\Omega = 6.23$,

TABLE 11. Calibrated Parameter Values

β	Discounting factor	0.96
α	Capital share	0.5
Ω	Investment adjustment cost	6.23
η	Frisch inverse elasticity	2
δ	Capital depreciation rate	0.10
ϵ	Elasticity of substitution in CES	11
Ω_p	Price adjustment parameter	60
κ	Fraction of profit endowed to new banks	0.25
ρ_e	Persistence of endowment process	0.95
ζ	Bankruptcy cost parameter	0.12
μ_s	SOE-specific TFP	0.55
μ_p	POE-specific TFP (normalized)	1
σ_s	SOE productivity dispersion	1.42
σ_p	POE productivity dispersion	1.70
$\tilde{\psi}$	Capital adequacy ratio	0.12
χ	Parameter in risk-adjusted weight	-0.4345
ξ	Parameter in risk-adjusted weight	0.5913
γ_m	parameter in money growth rule	0.391
γ_π	parameter in money growth rule	-0.397
γ_y^+	parameter in money growth rule	0.183
γ_y^-	parameter in money growth rule	-1.299

in line with the estimation in the DSGE literature (Smets and Wouters, 2007). We set $\kappa = 0.75$ such that 25% of the bank profits are allocated to entering banks as start-up funds. We assume that $\rho_e = 0.95$ in our baseline calibration. We set $\tilde{\psi} = 0.12$, in light with the CAR requirements for systemically important banks in China. We set the bankruptcy cost parameter to $\zeta = 0.12$, in line with Bernanke et al. (1999).

We calibrate the parameters in the money growth rule following the estimation of Chen et al. (2018). In particular, we set $\gamma_m = 0.391$, $\gamma_\pi = -0.397$, $\gamma_y^+ = 0.183$, and $\gamma_y^- = -1.299$.

We calibrate the remaining set of parameters $\{\xi, \chi, \mu_s, \sigma_s, \sigma_p\}$ by matching the model-implied moments with their counterparts in the data. We first use the firm-level data from China's Annual Survey of Industrial Firms for the period from 1998 to 2007 to construct the firm-level TFPs. We normalize the average TFP in the POE sector to $\mu_p = 1$, and then compute the ratio of the average TFP between SOEs and POEs to pin

down the value of μ_s . We use the average cross-sectional dispersion of firm-level TFPs to pin down the values of σ_j . This calibration procedure leads to $\mu_s = 0.55$, $\sigma_s = 1.42$ and $\sigma_p = 1.70$.²¹

To calibrate the parameters in the risk-weighting function $h(\omega_t) = \xi\omega_t^\chi$, we use the risk-adjusted weights on loans (denoted by h_t^{data}) and the share of safe loans (denoted by ω_t^{data}), both disclosed by China's Big Five banks. In particular, we regress the log of risk-adjusted weight $\log(h_t^{\text{data}})$ on $\log(\omega_t^{\text{data}})$ to estimate the coefficients ξ and χ . The procedure yields $\xi = 0.5913$ and $\chi = -0.4345$.²²

V.3. Transition dynamics and welfare following a monetary policy shock. We solve the model's transition dynamics following a monetary policy shock based on the calibrated parameters. We focus on a perfect foresight equilibrium. In period 0, the economy stays at the steady state. In period 1, an unexpected expansionary monetary policy shock hits the economy and there are no further shocks in subsequent periods.

Figure 4 displays the transition dynamics (or equivalently, impulse responses) of a few key macroeconomic variables in the benchmark model (the black solid lines) following a positive one standard deviation shock to monetary policy. The shock increases money supply, raising the bank leverage ratio. Under the CAR constraints, an increase in leverage requires the bank to reduce its asset risks (see Eq. (24)). Thus, the bank shifts lending to safe borrowers, increasing the share of SOE loans and lowering the bankruptcy ratio. However, since SOEs are less productive than POEs on average, allocating more credit to SOEs reduces aggregate TFP. The shock boosts aggregate demand, raising consumption and investment. While the increase in bank leverage further boosts investment, the decline in TFP partially offsets the expansionary effects.

To highlight the importance of endogenous risk-weighting of bank assets in the transmission channel of monetary policy, we consider a counterfactual economy in which the share of SOE loans ω_t is fixed at its steady state value. The transition dynamics in this counterfactual economy are shown in Figure 4 (the blue dashed lines). Under the CAR constraint, bank leverage is pinned down by the SOE loan share and thus it does not respond to the shock. The constant SOE loan share also implies that the bank is unable to reallocate credit to inefficient SOEs, such that aggregate TFP does not change. Similar to the benchmark model (the black solid lines), the expansionary policy shock raises consumption and investment and reduces the bankruptcy probability. However, the magnitude of the responses of both investment and the bankruptcy probability are greater than those in the benchmark model, reflecting the two opposing effects stemming

²¹See Appendix E.3.1 for more details.

²²See Appendix E.3.2 for more details.

from changes in bank leverage and in aggregate TFP under endogenous risk-weighting in the benchmark model.²³

The reallocation effect of monetary policy shocks under CAR constraints with endogenous risk-weighting reduces social welfare. To quantify the welfare effects, we measure the welfare along the transition paths following a monetary policy shock by computing the consumption equivalent for the representative household relative to the steady state (with no shocks). In particular, the welfare is the fraction of steady-state consumption required for the household to stay indifferent between an economy with the monetary policy shock and the steady-state economy. That is, we solve for the value of ϖ such that

$$\sum_{t=1}^{\infty} \beta^t \left(\log C_t - \tau_l \frac{L_t^{1+\eta}}{1+\eta} + \tau_m \log \frac{M_t}{P_t} \right) = \frac{1}{1-\beta} \left[\log (1 + \varpi) C - \tau_l \frac{L^{1+\eta}}{1+\eta} + \tau_m \log \frac{M}{P} \right], \quad (48)$$

where C , L and M/P are the steady-state consumption, labor hours and real money balances.

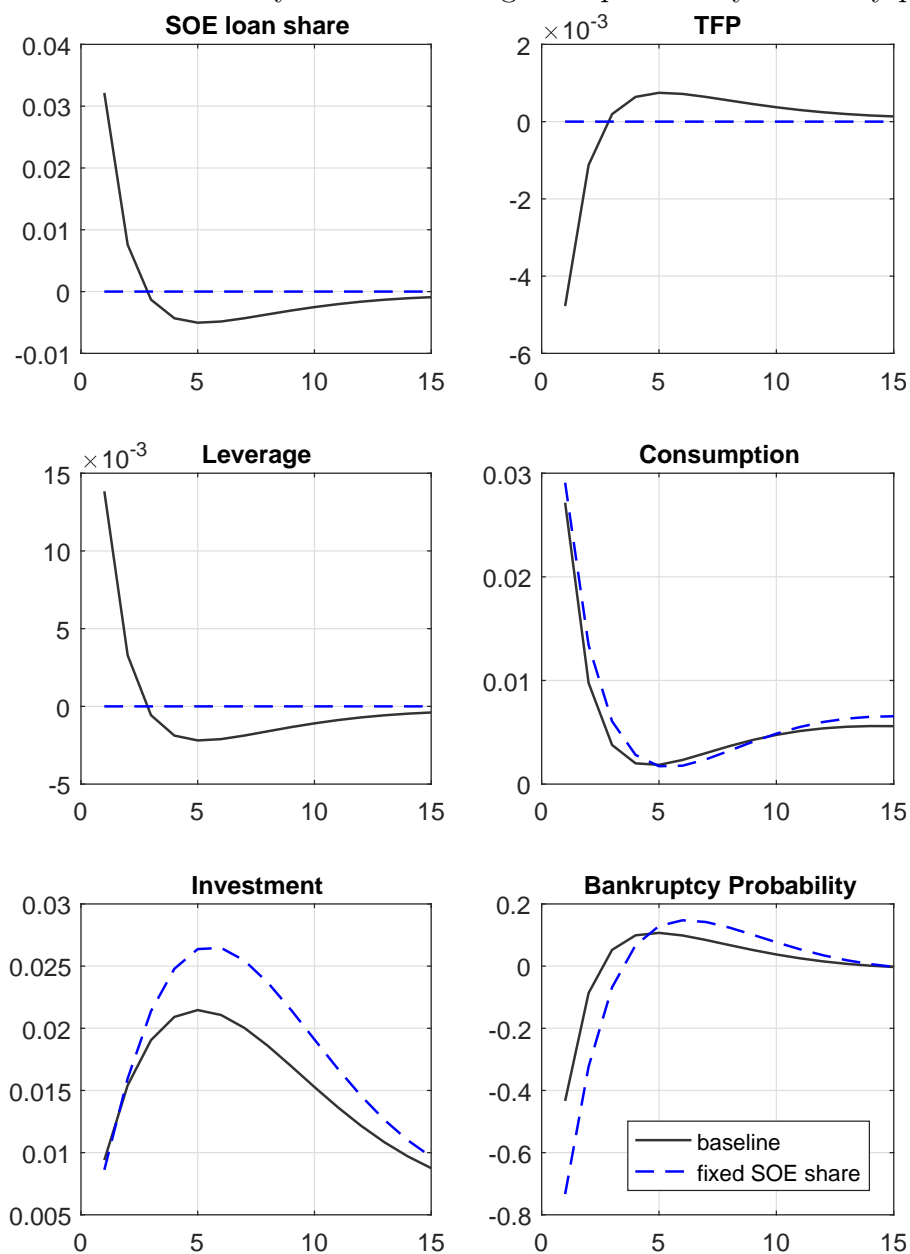
We compare the welfare in the benchmark model with that in the counterfactual with a fixed ω_t . Both versions of the model have the same steady state equilibrium, although the transition dynamics following a monetary policy shock differ. Our calculation shows that the expansionary monetary policy shock leads to a welfare gain of $\varpi = 0.27\%$ of steady-state consumption in the benchmark model. In the counterfactual model, the welfare gain is 0.33% of steady-state consumption. Thus, the endogenous risk-weighting channel leads to a modest welfare loss of about 0.06% of consumption equivalent units.

VI. CONCLUSION

We present robust evidence that the implementation of Basel III regulations in 2013 has significantly changed Chinese banks' risk-taking behaviors and their responses to monetary policy shocks. After the regulatory policy changes, banks reduced risk-taking by increasing the share of lending to SOEs, both on average and conditional on monetary policy expansions. The declines in bank risk-taking following a monetary policy expansion are both statistically significant and economically important. Our estimation suggests that a one standard deviation increase in the exogenous component of M2 growth raises the

²³To further illustrate the role of risk-weighting in the transmission of monetary policy shocks, we have considered an alternative risk-weighting function with a "penalty term" that allows for continuous variations in the magnitude of risk-weighting adjustments. We find that weakening the endogenous risk-weighting mechanism mitigates credit reallocations and enhances the stimulus effects of an expansionary monetary policy. See Appendix E.5 for details.

FIGURE 4. Transition dynamics following an expansionary monetary policy



Notes: This figure shows the dynamic responses to an expansionary monetary policy shock. The vertical axes show percentage deviations from the initial steady state (e.g., 0.01 corresponds to 1%). The horizontal axes show the periods after the impact period of the shock. The solid lines denote the responses in the benchmark model and the dashed lines are those in the counterfactual case with the SOE loan share ω_t held fixed at the steady state value.

probability of SOE lending by up to 27% 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. In a two-sector general equilibrium model calibrated to the Chinese data, we show that the bank risk-taking channel has quantitatively important macroeconomic implications. Consistent with our empirical evidence, the model predicts that an expansionary monetary policy shock raises bank lending to SOEs, leading to persistent TFP declines that partially offset the expansionary effects of the shock.

Although our data are from China, the general implications of our findings for the interconnection between monetary policy, financial stability, and capital allocation efficiency are not specific to that country. Our evidence suggests that tightening capital regulations helps reduce bank risk-taking following monetary policy expansions, alleviating concerns about financial stability. 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. Our paper does not address optimal policy issues in such an environment. However, the tradeoff between bank risk-taking and capital reallocations identified in our study is likely to play an important role for designing optimal macroeconomic stabilization policies.

APPENDIX A. PROOFS OF PROPOSITIONS

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

A.1. Proof of Proposition 1.

Proof. We first show that $\frac{\partial \sigma}{\partial \psi} < 0$.

The optimizing condition (12) can be written as

$$g(\sigma; r, \psi) = 0, \quad (\text{A.1})$$

where $g(\sigma; r, \psi) = \sigma \frac{\partial \log[\bar{R}(\sigma) - R^*(\sigma; \psi)]}{\partial \sigma} - \frac{1+\rho}{2}$ and $\frac{\partial \log[\bar{R}(\sigma) - R^*(\sigma; \psi)]}{\partial \sigma} = \frac{\phi_1 - 2\phi_2\sigma + \frac{1}{2} + \rho r \psi \sigma^{\rho-1}}{(\phi_1 - \phi_2\sigma + \frac{1}{2})\sigma - r(1 - \psi\sigma^\rho)}$.

It can be further simplified into

$$g(\sigma; r, \psi) = \frac{v(\sigma; r, \psi)}{2[(\phi_1 - \phi_2\sigma + \frac{1}{2})\sigma - r(1 - \psi\sigma^\rho)]}, \quad (\text{A.2})$$

where

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

Therefore, $g(\sigma; r, \psi) = 0$ is equivalent to $v(\sigma; r, \psi) = 0$. Under the CAR constraint, we have $\frac{c}{k} = \psi\sigma^\rho < 1$. Then, we have

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

The last equation implies that $v(\sigma; r, \psi) > 0$ for any $\sigma \in (0, \hat{\sigma})$, where $\hat{\sigma} \equiv \frac{(1 - \rho)(\phi_1 + \frac{1}{2})}{(3 - \rho)\phi_2}$.

Moreover, for any $\sigma \in [\hat{\sigma}, \bar{\sigma})$ we have

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

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

$$v_\sigma \leq -(1 - \rho)\left(\phi_1 + \frac{1}{2}\right) - (1 - \rho)\rho r \psi \sigma^{\rho-1} < 0. \quad (\text{A.4})$$

We also have

$$v(\hat{\sigma}; r, \psi) = (1 + \rho)r - (1 - \rho)r\psi\hat{\sigma}^\rho > 2\rho r > 0, \quad (\text{A.5})$$

and

$$\begin{aligned} v(\bar{\sigma}; r, \psi) &= -(3 - \rho)\phi_2\bar{\sigma}^2 + (1 - \rho)\left(\phi_1 + \frac{1}{2}\right)\bar{\sigma} + (1 + \rho)r - (1 - \rho)r\psi\bar{\sigma}^\rho \\ &= -\rho[\bar{R}(\bar{\sigma}) - r] - (1 - \rho)r\psi\bar{\sigma}^\rho < 0. \end{aligned} \quad (\text{A.6})$$

The second line for $v(\bar{\sigma}; r, \psi)$ is obtained by using $3\phi_2\bar{\sigma}^2 = (\phi_1 + \frac{1}{2})\bar{\sigma} + r$. 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 now show that $\frac{d\sigma}{d\psi} < 0$. From $v(\sigma; r, \psi) = 0$, we have $\frac{d\sigma}{d\psi} = -\frac{v_\psi}{v_\sigma}$. Since $v_\psi = -(1 - \rho)r\sigma^\rho < 0$ and $v_\sigma < 0$ 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 $v = -(3 - \rho)\phi_2\sigma^2 + (1 - \rho)(\phi_1 + \frac{1}{2})\sigma + (1 + \rho)r - (1 - \rho)r\psi\sigma^\rho = 0$, we have

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

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,

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

□

A.2. Proof of Proposition 2.

Proof. Applying the implicit function theorem to $v(\sigma; r, \psi) = 0$ yields

$$\frac{d\sigma}{dr} = -\frac{v_r}{v_\sigma} = -\frac{(1 + \rho) - (1 - \rho)\psi\sigma^\rho}{v_\sigma}, \quad (\text{A.7})$$

where v_σ is given by (A.4). The second equality is from the definition of v_r . Notice that under the binding CAR constraint, we have $\lambda = \frac{1}{\psi\sigma^\rho} > 1$ and $v_\sigma < 0$, therefore $(1 + \rho) - (1 - \rho)\frac{\sigma^\rho}{\psi} > 0$ implying $\frac{d\sigma}{dr} > 0$. Moreover, from the CAR constraint we have

$$\frac{d\lambda}{dr} = -\frac{\rho}{\psi\sigma^{\rho-1}} \frac{d\sigma}{dr} < 0. \quad (\text{A.8})$$

□

A.3. Proof of Proposition 3.

Proof. 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.4). To further simplify the last equation, from $v(\sigma; r, \psi) = 0$, we have

$$-(3-\rho) \phi_2 \sigma = -\frac{(1+\rho)r}{\sigma} \left(1 - \frac{1-\rho}{1+\rho} \psi \sigma^\rho \right) - (1-\rho) \left(\phi_1 + \frac{1}{2} \right). \quad (\text{A.9})$$

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

$$\frac{\partial^2 \sigma}{\partial r \partial \psi} = -\frac{1-\rho}{v_\sigma^3} \sigma^\rho \Psi, \quad (\text{A.10})$$

where

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

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

$$\Psi = -(3-\rho) \phi_2 \sigma \left[(3-\rho) \phi_2 \sigma + \frac{\rho(1+\rho)r}{\sigma} \right] - (1+\rho) \frac{r}{\sigma} \left(1 - \frac{1-\rho}{1+\rho} \psi \sigma^\rho \right) \Xi, \quad (\text{A.11})$$

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

$$\Xi > (3-\rho) \phi_2 (\rho+1) \sigma - (1-\rho)(1+\rho) \left(\phi_1 + \frac{1}{2} \right) > 0, \quad (\text{A.12})$$

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

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

where

$$\begin{aligned} v_\sigma &= -2(3 - \rho)\phi_2\sigma + (1 - \rho)\left(\phi_1 + \frac{1}{2}\right) - \rho(1 - \rho)r\psi\sigma^{\rho-1} < 0 \\ v_r &= (1 + \rho) - (1 - \rho)\psi\sigma^\rho > 0 \\ v_\rho &= \phi_2\sigma^2 - \left(\phi_1 + \frac{1}{2}\right)\sigma + r + r\psi\sigma^\rho - (1 - \rho)r\psi\sigma^\rho \log \sigma < 0 \\ v_{r\sigma} &= -\rho(1 - \rho)\psi\sigma^{\rho-1} < 0 \\ v_{r\rho} &= 1 + \psi\sigma^\rho - (1 - \rho)\psi\sigma^\rho \log \sigma > 0 \\ v_{\sigma\rho} &= 2\phi_2\sigma - \left(\phi_1 + \frac{1}{2}\right) - (1 - 2\rho)r\psi\sigma^{\rho-1} - \rho(1 - \rho)r\psi\sigma^{\rho-1} \log \sigma \\ v_{\sigma\sigma} &= -2(3 - \rho)\phi_2 + \rho(1 - \rho)^2 r\psi\sigma^{\rho-2} \end{aligned}$$

First,

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

Second,

$$\begin{aligned} &v_{r\sigma}v_\rho + v_rv_{\sigma\rho} - v_\sigma v_{r\rho} \\ &= -\rho(1 - \rho)\psi\sigma^\rho \left[\phi_2\sigma - \left(\phi_1 + \frac{1}{2}\right) + \frac{r}{\sigma} + r\psi\sigma^{\rho-1} \left(1 - (1 - \rho)\log \sigma\right) \right] \\ &\quad + \left[(1 + \rho) - (1 - \rho)\psi\sigma^\rho \right] \left[2\phi_2\sigma - \left(\phi_1 + \frac{1}{2}\right) - (1 - \rho)r\psi\sigma^{\rho-1} + \rho r\psi\sigma^{\rho-1} \left(1 - (1 - \rho)\log \sigma\right) \right] \\ &\quad + \left[2(3 - \rho)\phi_2\sigma - (1 - \rho) \left(\phi_1 + \frac{1}{2}\right) + \rho(1 - \rho)r\psi\sigma^{\rho-1} \right] \left[1 + \psi\sigma^\rho \left(1 - (1 - \rho)\log \sigma\right) \right] \\ &= 8\phi_2\sigma - 2 \left(\phi_1 + \frac{1}{2}\right) + (1 - \rho)(1 + \rho)\psi\sigma^\rho \left[\left(\phi_1 + \frac{1}{2}\right) - \frac{2 + \rho}{1 + \rho}\phi_2\sigma - \frac{r}{\sigma} \left(1 - \frac{1 - \rho}{1 + \rho}\psi\sigma^\rho\right) \right] \\ &\quad + \psi\sigma^\rho \left[1 - (1 - \rho)\log \sigma \right] \left[2(3 - \rho)\phi_2\sigma - (1 - \rho) \left(\phi_1 + \frac{1}{2}\right) + \rho(1 + \rho) \frac{r}{\sigma} \left(1 - \frac{1 - \rho}{1 + \rho}\psi\sigma^\rho\right) \right] \\ &= 8\phi_2\sigma - 2 \left(\phi_1 + \frac{1}{2}\right) + (1 - \rho)\psi\sigma^\rho \left[2\left(\phi_1 + \frac{1}{2}\right) - 5\phi_2\sigma \right] \end{aligned}$$

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

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

$$\begin{aligned} \left[8 - 5(1 - \rho) \psi \sigma^\rho \right] \phi_2 \hat{\sigma} - 2 \left[1 - (1 - \rho) \psi \sigma^\rho \right] \left(\phi_1 + \frac{1}{2} \right) &> 0 \\ (1 - \rho) \left[8 - 5(1 - \rho) \psi \sigma^\rho \right] - 2(3 - \rho) \left[1 - (1 - \rho) \psi \sigma^\rho \right] &> 0 \\ 2(1 - 3\rho) + \psi \sigma^\rho (1 - \rho)(1 + 3\rho) &> 0 \end{aligned}$$

which holds for relatively small ρ .

Thus, we obtain

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

□

APPENDIX B. 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.²⁴

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*.

²⁴For 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>.

The RW approach assigns ad hoc risk weights to different categories of loans, independent of credit risks.²⁵ 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*.²⁶ 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.²⁷ 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 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 B.1, which shows the CAR disclosure from the 2013 annual report of the Bank of China (BoC), one of the Big Five, and the Bank of China Group.

APPENDIX C. CLUSTERED STANDARD ERRORS

In the text, we have reported regression results with robust standard errors. However, the results are robust when the standard errors are clustered by firms or by bank branches, as shown in Table C.1 below.

APPENDIX D. 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

²⁵For example, the risk weight on a commercial bank’s claims on corporates is 100%, regardless of the firms’ credit rating.

²⁶The 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.

²⁷For 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.

TABLE B.1. Capital and Capital Adequacy Ratios

	End of 2014		End of 2013	
	BoC Group	BoC	BoC Group	BoC
CAR based on IRB approach under the new (2012) <i>Capital Rules</i>				
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.

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

$$\ln \frac{Y_{it}}{L_{it}} = \gamma + \alpha \ln \frac{K_{it}}{L_{it}} + \varepsilon_{it}. \quad (\text{D.1})$$

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

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

TABLE C.1. Clustered standard errors

$SOE_{i,j,t}$	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	Probit	Probit	Probit
$RiskM_j \times Post_y$	0.0021 (0.0055) [0.0055]	0.0032 (0.0057) [0.0059]	0.0008 (0.0048) [0.0055]	0.0017 (0.0057) [0.0055]	0.0034 (0.0059) [0.0059]	0.0038 (0.0044) [0.0046]
$RiskM_j \times MP_t \times Post_y$	2.3049 (0.7805)*** [0.9293]**	3.0030 (0.8574)*** [1.0595]***	2.1395 (0.7204)*** [0.8055]***	1.9802 (0.8107)** [0.8738]**	2.6741 (0.8848)*** [0.9928]***	1.9530 (0.7086)*** [0.7074]***
$RiskM_j \times MP_t$	10.0256 (4.0150)** [4.8672]**	13.3474 (4.174)*** [4.9795]***	8.6351 (3.5917)** [3.8820]**	8.2457 (4.2723)* [4.7563]*	11.7884 (4.5043)** [4.9347]**	8.1688 (3.6969)** [3.8112]**
$RiskM_j \times MP_t \times CAR_t$	-0.8146 (0.3229)** [0.39215]**	-1.0736 (0.3422)*** [0.4039]***	-0.6907 (0.2945)** [0.3200]**	-0.6697 (0.3473)* [0.3850]*	-0.9536 (0.3783)** [0.4108]**	-0.6949 (0.3123)** [0.3245]**
$RiskM_j \times CAR_t$	0.0011 (0.0025) [0.0029]	0.0007 (0.0028) [0.0030]	-0.0002 (0.0021) [0.0024]	0.0012 (0.0026) [0.0027]	0.0004 (0.0028) [0.0031]	-0.0011 (0.0020) [0.0024]
$RiskM_j \times MP_t \times AveFloat_t$		-2.1223 (5.5344) [6.238]	-3.1430 (4.7440) [5.8690]		-1.0822 (5.7853) [6.7670]	2.6869 (4.6055) [5.7971]
$RiskM_j \times AveFloat_t$		0.0937 (0.0540) [0.0695]	0.0119 (0.0451) [0.0593]		0.1026 (0.0566)* [0.0716]	0.0319 (0.0429) [0.0497]
Observations	365,684	365,684	320,311	347,129	347,129	296,325
R-squared	0.251	0.251	0.403	0.333	0.333	0.491
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
Initial profit \times year FE	no	no	yes	no	no	yes
Initial SOE \times year FE	no	no	yes	no	no	yes
Industry FE	no	no	yes	no	no	yes

Notes: The numbers in the parentheses show the standard errors clustered by firms. The numbers in the squared brackets show the standard errors clustered by bank branches. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

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 E. DETAILS OF THE DYNAMIC MODEL

This section summarizes the full dynamic system for the quantitative model, outlines our approach to solving the model's steady state equilibrium, provides some details of parameter calibration, and describes how we aggregate the distributions of investment returns across sectors.

E.1. Summary of the full dynamic system.

Banking Sector.

- (1) Flow of funds constraint:

$$Q_t K_{t+1} = e_t + D_t. \quad (\text{E.1})$$

- (2) The marginal product of effective capital r_t is defined as

$$r_{t+1} = \alpha \left(\frac{1 - \alpha}{W_{t+1}/p_{t+1}^m} \right)^{\frac{1-\alpha}{\alpha}} = \alpha \frac{p_t^m Y_{t+1}}{\tilde{K}_{t+1}}. \quad (\text{E.2})$$

- (3) Leverage ratio λ_t is defined as

$$\lambda_t = \frac{Q_t K_{t+1}}{e_t}. \quad (\text{E.3})$$

- (4) The CAR is defined as

$$\psi_t = \frac{e_t}{h(\omega_t) Q_t K_{t+1}} = \tilde{\psi}, \quad (\text{E.4})$$

where the risk-adjusted weight $h(\omega_t)$ is given by

$$h(\omega_t) = \xi \omega_t^\chi. \quad (\text{E.5})$$

- (5) The cutoff of investment efficiency z_t^* is defined as

$$z_t^* \equiv \frac{R_t^d \left(1 - \frac{1}{\lambda_t}\right) - (1 - \delta) Q_{t+1}/Q_t}{r_{t+1}/Q_t}. \quad (\text{E.6})$$

- (6) For PDF of z_t , we use the log-normal distribution to approximate it. In particular, $f(z; \omega_t)$ satisfies

$$f(z; \omega_t) = \frac{1}{z \sigma_t \sqrt{2\pi}} \exp \left\{ -\frac{(\log z - \mu_t)^2}{2\sigma_t^2} \right\}, \quad (\text{E.7})$$

where

$$\mu_t = \log \left(\frac{\mu_{zt}^2}{\sqrt{\mu_{zt}^2 + \sigma_{zt}^2}} \right), \quad (\text{E.8})$$

$$\sigma_t^2 = \log \left(1 + \frac{\sigma_{zt}^2}{\mu_{zt}^2} \right), \quad (\text{E.9})$$

$$\mu_{zt} = \omega_t \tilde{\mu}_s + (1 - \omega_t) \tilde{\mu}_p, \quad (\text{E.10})$$

$$\sigma_{zt}^2 = \omega_t^2 \tilde{\sigma}_s^2 + (1 - \omega_t)^2 \tilde{\sigma}_p^2. \quad (\text{E.11})$$

(7) The optimal decision for SOE loan share ω_t satisfies

$$-\frac{h'(\omega_t)}{h(\omega_t)} \int_{z > z_t^*} (z - z_t^*) f(z; \omega_t) dz = - \int_{z > z_t^*} (z - z_t^*) \frac{\partial f(z; \omega_t)}{\partial \omega_t} dz + \frac{\partial z_t^*}{\partial \omega_t} \int_{z > z_t^*} f(z; \omega_t) dz, \quad (\text{E.12})$$

where

$$\frac{\partial z_t^*}{\partial \omega_t} = -\tilde{\psi} h'(\omega_t) Q_t \frac{R_t^d}{r_{t+1}}. \quad (\text{E.13})$$

(8) The profit V_t in the banking sector is

$$V_t = \frac{r_t}{Q_{t-1}} \lambda_{t-1} e_{t-1} \int_{z > z_{t-1}^*} (z - z_{t-1}^*) f(z; \omega_{t-1}) dz. \quad (\text{E.14})$$

(9) Government spending on the deposit insurance G_t is given by

$$G_t = R_{t-1}^d d_{t-1} \int_{z < z_{t-1}^*} f(z; \omega_{t-1}) dz - (1 - \zeta) k_t \int_{z < z_{t-1}^*} [r_t z + (1 - \delta) Q_t] f(z; \omega_{t-1}) dz. \quad (\text{E.15})$$

(10) The bankruptcy cost satisfies

$$\Psi_t = \zeta \int_{z < z_{t-1}^*} [r_t z + (1 - \delta) Q_t] k_t f(z; \omega_{t-1}) dz. \quad (\text{E.16})$$

(11) Net worth of new banks evolves according to

$$e_t = \rho_e e_{t-1} + (1 - \rho_e) \kappa V_t. \quad (\text{E.17})$$

Household and Monetary Policy.

(1) Euler equation for saving (for real deposit R_t^d)

$$1 = \beta \frac{\Lambda_{t+1}}{\Lambda_t} R_t^d, \quad (\text{E.18})$$

where

$$\Lambda_t = \frac{1}{C_t}. \quad (\text{E.19})$$

(2) Labor supply (L_t)

$$W_t \Lambda_t = \chi L_t^\eta. \quad (\text{E.20})$$

(3) Nominal interest rate is exogenously determined by the government

$$R_{t+1}^n = R_{t+1}^d \pi_{t+1}, \quad (\text{E.21})$$

where inflation is defined as

$$\pi_{t+1} = \frac{P_{t+1}}{P_t}. \quad (\text{E.22})$$

(4) Demand for money

$$1 = \tau_m \frac{P_t}{\Lambda_t M_t} + \beta \frac{\Lambda_{t+1}}{\Lambda_t} \frac{P_t}{P_{t+1}}. \quad (\text{E.23})$$

Final Goods and Retail Sectors.

(1) Optimal pricing P_t^m

$$\frac{P_t^m}{P_t} = \frac{\epsilon - 1}{\epsilon} + \frac{\Omega_p}{\epsilon} \left[\left(\frac{\pi_t}{\pi} - 1 \right) \frac{\pi_t}{\pi} - \beta \frac{\Lambda_{t+1}}{\Lambda_t} \left(\frac{\pi_{t+1}}{\pi} - 1 \right) \frac{\pi_{t+1}}{\pi} \right]. \quad (\text{E.24})$$

Capital Goods Producer.

(1) Capital goods supply:

$$Q_t = 1 + \frac{\Omega}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 + \Omega \left(\frac{I_t}{I_{t-1}} - 1 \right) \frac{I_t}{I_{t-1}} - \beta \frac{\Lambda_{t+1}}{\Lambda_t} \Omega \left(\frac{I_{t+1}}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2. \quad (\text{E.25})$$

Aggregation and General Equilibrium.

(1) Aggregate output

$$Y_t = \tilde{K}_t^\alpha L_t^{1-\alpha}, \quad (\text{E.26})$$

where \tilde{K}_t is the aggregate effective units of capital.

(2) Aggregate labor demand

$$L_t = \left(\frac{1 - \alpha}{W_t/p_t^m} \right)^{\frac{1}{\alpha}} \tilde{K}_t. \quad (\text{E.27})$$

(3) Aggregate effective capital

$$\tilde{K}_t = \mu_{zt-1} K_t, \quad (\text{E.28})$$

where $\mu_{zt-1} = \omega_{t-1} \tilde{\mu}_s + (1 - \omega_{t-1}) \tilde{\mu}_p$.

(4) Capital accumulation

$$K_{t+1} = (1 - \delta) K_t + I_t, \quad (\text{E.29})$$

(5) Resource constraint

$$C_t + \left[1 + \frac{\Omega}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t + \Psi_t = Y_t. \quad (\text{E.30})$$

E.2. Solving the Steady State. We now present the steps for solving the steady state. We set the inflation rate in the steady state to be $\pi = 1$. We normalize the aggregate price in the steady state P to be 1. In the steady state, the relative price of intermediate goods is $p^m = \frac{\epsilon-1}{\epsilon}$.

From (E.18) and the definition of nominal interest rate, we obtain the deposit rate in the steady state $R^d = R^n = \frac{1}{\beta}$.

Take the steady-state SOE loan share ω and capital K as two unknown variables. Given the value of ω and K , we solve other endogenous variables. In the last step, we will solve ω and K from a two-variable equation system.

We specify the steady state labor supply as $L = 0.33$. From the definition of effective capital (E.28), we obtain $\tilde{K} = [\omega\tilde{\mu}_s + (1-\omega)\tilde{\mu}_p]K$. From the aggregate production (E.26), we can solve aggregate output $Y = \tilde{K}^\alpha L^{1-\alpha}$.

From (E.25), the steady state capital price satisfies $Q = 1$. From (E.2), we have $r = \alpha \frac{p^m Y}{\tilde{K}}$.

We can solve the leverage ratio as $\lambda = \frac{1}{h(\omega)\tilde{\psi}}$, where $h(\omega) = \xi\omega^\chi$. The cutoff satisfies $z^* \equiv \frac{R^d(1-\frac{1}{\lambda})-(1-\delta)}{r/Q}$.

Given z^* and ω , we can obtain the following auxiliary terms: $\int_{z>z^*} (z - z^*) f(z; \omega) dz$, $\frac{\partial f(z; \omega)}{\partial \omega}$ and $\frac{\partial z^*}{\partial \omega} = -\tilde{\psi} h'(\omega) \frac{R^d}{r}$. The profit in banking sector is $V = R^k K \int_{z>z^*} (z - z^*) f(z; \omega) dz$. The endowment satisfies $e = \kappa V$.

From the optimal decision for ω_t and the CAR constraint

$$\begin{aligned} -\frac{h'(\omega)}{h(\omega)} \int_{z>z^*} (z - z^*) f(z; \omega) dz &= -\int_{z>z^*} (z - z_t^*) \frac{\partial f(z; \omega)}{\partial \omega} dz + \frac{\partial z^*}{\partial \omega} \int_{z>z^*} f(z; \omega) dz, \\ \frac{e}{h(\omega) K} &= \tilde{\psi}, \end{aligned} \quad (\text{E.32})$$

we can solve two-unknown variables ω and K .

From the capital accumulation process, we can solve the investment

$$I = [1 - (1 - \delta)] K. \quad (\text{E.33})$$

From the flow of funds constraint, we can solve the deposit as $D = K - e$. From the resource constraint, we can solve the consumption as

$$C = Y - I - \Psi. \quad (\text{E.34})$$

From the labor demand function (E.27), we can solve real wage rate as

$$W = (1 - \alpha) \left(\frac{\tilde{K}}{L} \right)^\alpha p^m. \quad (\text{E.35})$$

From the labor supply function, we can pin down the parameter χ as

$$\chi = \frac{W}{CL^\eta}. \quad (\text{E.36})$$

From the money demand function, we have

$$M = \frac{\tau_m}{1-\beta}C. \quad (\text{E.37})$$

E.3. Calibration Details. This section describes our approach to calibrating the TFP distribution parameters for each sector and the parameters in the risk-weighting function in our dynamic model.

E.3.1. Calibrating sector-level TFP distributions. We first discuss the procedure for the calibration of sectoral TFP distribution. We use the Annual Survey of Industrial Firms conducted by China's National Bureau of Statistics for calibrating the model parameters. The survey data cover all the state-owned firms and non-state firms with sales above 5 million RMB from 1998-2007. We clean up the sample by discarding some observations with extreme or implausible values. Liu et al. (2020) give more descriptions about the dataset we use.

We compute firm-level TFP based on the production function, using data on capital and labor inputs and value-added output. In particular, the production function for firm i in industry m takes Cobb-Douglas form that used in the model

$$y_{mit} = (z_{mit}k_{mit})^\alpha (l_{mit})^{1-\alpha}, \quad (\text{E.38})$$

where y_{mit} denotes output, k_{mit} and l_{mit} denote the inputs of capital and labor, respectively, and z_{mit} denotes the firm-level TFP. The parameter $\alpha \in (0, 1)$ denotes the capital share. We assume that all the firms face the same production function parameters, which are calibrated at $\alpha = 0.5$. The production function implies that the firm-level TFP for j -type firms z_i^j , $j \in \{s, p\}$, is given by

$$z_{mit}^j = \left[\frac{y_{mit}^j}{(k_{mit}^j)^\alpha (l_{mit}^j)^{1-\alpha}} \right]^{\frac{1}{\alpha}}, \quad (\text{E.39})$$

where we measure the firm's output by value added, capital input by the value of fixed assets, and labor input by its employment size.²⁸

After obtaining the firm-level TFP, we can compute the industry-level TFP for POEs using the relation

$$\bar{z}_{mt}^p = \frac{1}{N_{mt}^p} \sum_i z_{mit}^p, \quad (\text{E.40})$$

²⁸The units of value added, fixed assets are expressed in trillions of RMB. The unit of employment is in millions of workers. SOEs are defined based on the firms' registration code "141", "143" and "151".

where \bar{z}_{mt}^p denotes the industry-level TFP for POE firms in industry m , N_{mt}^p denotes the number of POE firms in industry m , and year t . We normalize a firm's idiosyncratic component of productivity to be $\tilde{z}_{mit}^j = \frac{z_{mit}^j}{\bar{z}_{mt}^p}$, which corresponds to the \tilde{z}_j in our baseline model. We then compute the economy-wide average TFP for j -type firms \bar{z}_t^j as the average of the scaled industry-level TFP. In particular, TFP for j -type firms is given by

$$\bar{z}_t^j = \frac{1}{M_t} \sum_m \left(\frac{1}{N_{mt}^j} \sum_i \tilde{z}_{mit}^j \right), \quad j \in \{s, p\}. \quad (\text{E.41})$$

Notice that according to the definition of \tilde{z}_{mit}^j , the average of the industry-level TFP for POE firms $\frac{1}{N_{mt}^j} \sum_i \frac{1}{N_{mt}^j} \tilde{z}_{mit}^j$ is 1, so we set $\mu_p = 1$. To calibrate μ_s , we compute the average value of \bar{z}_t^s over the sample years (1998-2007), which is 0.55, so we set $\mu_s = 0.55$. To calibrate σ_j , we compute the economy-wide standard deviation of \tilde{z}_{mit}^j , and obtain $\sigma(\bar{z}_{mit}^s) = 1.42$ and $\sigma(\bar{z}_{mit}^p) = 1.70$. So we calibrate $\sigma_s = 1.42$ and $\sigma_p = 1.70$.

E.3.2. Calibrating the risk weighting function. We use the information from the bank-level risk-adjusted weight h_t^i and the share of safe loans ω_t^i for bank i in year t to calibrate the parameters in the risk weighting function $h_t^i = \xi \omega_t^\chi$. The risk weighting function can be written in log terms as

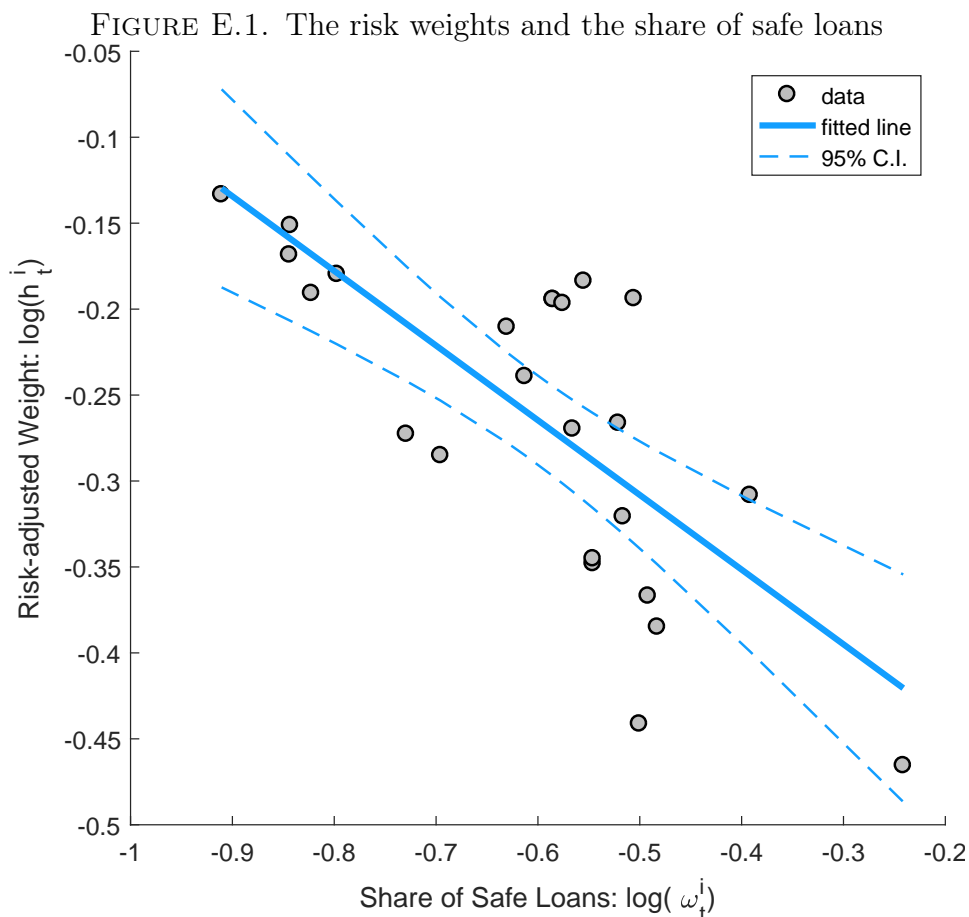
$$\log(h_t^i) = \log(\xi) + \chi \log(\omega_t^i). \quad (\text{E.42})$$

To calibrate parameters ξ and χ , we regress the observed $\log(h_t^i)$ on a constant and the observed $\log(\omega_t^i)$.

The data that we use are from the annual CAR reports issued by the Big Five banks over the periods of 2014 to 2018. The risk-adjusted weight h_t^i for bank i in year t is measured by the average weight for the non-retail risk exposure at the bank level.²⁹ The annual CAR report for individual bank discloses the detailed information of non-retail risk exposure based on the internal ratings approach. Each bank classifies the loans into different ratings according to the default risks. We define those loans with default probability below 1% as safe loans. We then measure ω_t^i by the share of safe loans in all loans for bank i in year t . The sample covers the Big Five banks for the years from 2013 to 2017, the periods after China's implementation of Basel III regulations.

Figure E.1 shows a scatter plot of the risk weights and the share of safe loans in the data (both in natural log terms), along with the fitted line. We use these observed data to estimate the empirical specification in Eq. (E.42) using the OLS approach. We obtain a point estimate of the intercept of -0.5254 and a slope of -0.4345 , both statistically

²⁹According to the annual CAR report of commercial banks, the non-retail risk exposure includes loans issued to corporations, public institutions and professional loan customers.



Notes: This figure plots the risk-adjusted weights against the share of safe loan, both in natural log terms, along with the fitted line (the solid line) and the 95% confidence intervals (the area between the dashed lines). Each point represents a pair of the share of safe loan and the corresponding risk-adjusted weight for a given bank in a particular year. The sample covers the Big Five banks for the years from 2013 to 2017, after China’s implementation of Basel III regulations.

significant at the 99% confidence level. These estimates imply that $\xi = \exp(-0.5254) = 0.5913$ and $\chi = -0.4345$, which are the calibrated values that we use for solving the dynamic model.

E.4. Approximation of the Sum of Log-normal Random Variables. In the quantitative exercise, considering the sum of two independently distributed lognormal random variables (RVs) is too computationally time consuming. To alleviate the computational burden, we follow Pratesi et al. (2006) to use the log-normal distribution to approximate the PDF of z_t . The mathematical problem can be described as follows. We have two RVs \tilde{z}_j that follows log-normal distribution with mean $\tilde{\mu}_j$ and standard deviation $\tilde{\sigma}_j$. Then,

the portfolio of two assets has the return

$$z = \sum_{j=\{s,p\}} \omega_j \tilde{z}_j, \quad (\text{E.43})$$

where $\omega_s = \omega$ and $\omega_p = 1 - \omega$. We use a log normal distribution to approximate the true distribution of z , i.e., $\log(z)$ approximately follows $\mathbf{N}(\mu, \sigma^2)$. We need to derive the formula for μ and σ^2 as functions of $\tilde{\mu}_j$ and $\tilde{\sigma}_j^2$.

The mean of z satisfies

$$\mu_z = \mathbf{E} \left[\sum_{j=\{s,p\}} \omega_j \tilde{z}_j \right] = \sum_{j=\{s,p\}} \omega_j \mathbf{E}(\tilde{z}_j) = \omega \tilde{\mu}_s + (1 - \omega) \tilde{\mu}_p. \quad (\text{E.44})$$

The variance of z satisfies

$$\sigma_z^2 = \mathbf{Var} \left(\sum_{j=\{s,p\}} \omega_j \tilde{z}_j \right) = \sum_{j=\{s,p\}} \omega_j^2 \tilde{\sigma}_j^2. \quad (\text{E.45})$$

Therefore, the RV $\log(z)$ follows $\mathbf{N}(\mu, \sigma^2)$ where μ and σ^2 satisfies

$$\mu = \log \left(\frac{\mu_z^2}{\sqrt{\mu_z^2 + \sigma_z^2}} \right), \quad (\text{E.46})$$

$$\sigma^2 = \log \left(1 + \frac{\sigma_z^2}{\mu_z^2} \right). \quad (\text{E.47})$$

The PDF of z is

$$f(z, \omega) = \frac{1}{z\sigma\sqrt{2\pi}} \exp \left\{ -\frac{(\log z - \mu)^2}{2\sigma^2} \right\}. \quad (\text{E.48})$$

Then, we have

$$\frac{\partial f(z, \omega)}{\partial \omega} = \frac{1}{\sigma} f(z, \omega) \left\{ \left[\frac{(\log z - \mu)^2}{\sigma^2} - 1 \right] \frac{\partial \sigma}{\partial \omega} + \frac{\log z - \mu}{\sigma} \frac{\partial \mu}{\partial \omega} \right\}, \quad (\text{E.49})$$

where

$$\begin{aligned} \frac{\partial \mu}{\partial \omega} &= \left[\frac{2}{\mu_z^2} - \frac{1}{\mu_z^2 + \sigma_z^2} \right] \mu_z \frac{\partial \mu_z}{\partial \omega} - \frac{1}{2(\mu_z^2 + \sigma_z^2)} \frac{\partial \sigma_z^2}{\partial \omega}, \\ \frac{\partial \sigma}{\partial \omega} &= \frac{1}{2\sigma} \frac{1}{\mu_z^2 + \sigma_z^2} \left(\frac{\partial \sigma_z^2}{\partial \omega} - 2 \frac{\sigma_z^2}{\mu_z} \frac{\partial \mu_z}{\partial \omega} \right), \\ \frac{\partial \mu_z}{\partial \omega} &= \tilde{\mu}_s - \tilde{\mu}_p, \\ \frac{\partial \sigma_z^2}{\partial \omega} &= 2\omega \tilde{\sigma}_s^2 - 2(1 - \omega) \tilde{\sigma}_p^2. \end{aligned}$$

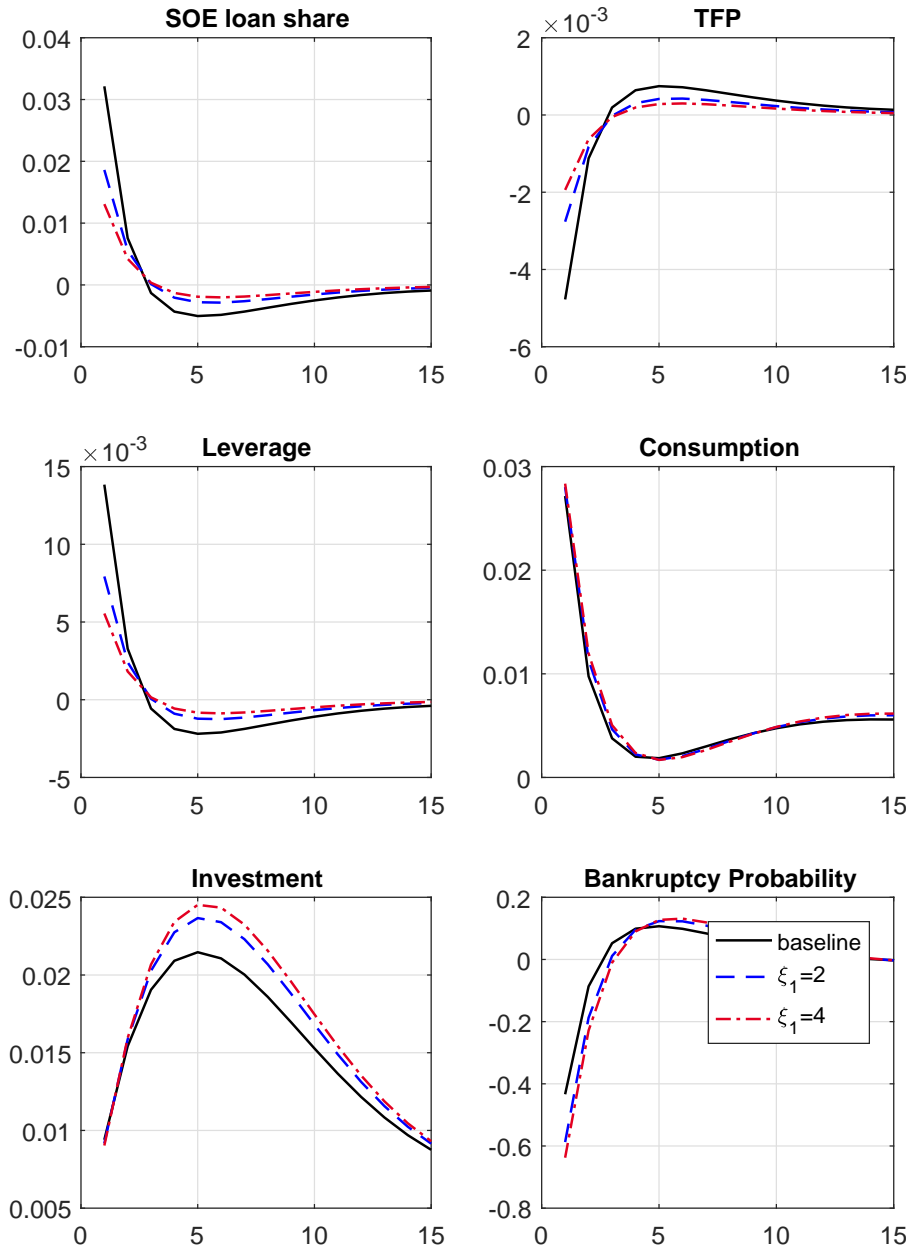
E.5. An alternative risk-weighting function. To further illustrate the role of risk-weighting in monetary policy transmission, we consider a more flexible form of the risk-weighting function with a penalty term for adjusting the SOE loan share. In particular, we assume that the risk-weighting function is given by

$$h(\omega_t) = \xi\omega_t^x + \frac{\xi_1}{2}(\omega_t - \omega)^2, \quad (\text{E.50})$$

where $\xi_1 \geq 0$ is the penalty parameter. A larger value of ξ_1 implies a higher cost for ω_t to deviate from its steady state value. In one extreme with $\xi_1 = \infty$, the SOE loan share ω_t would stay constant at the steady state, as in the counterfactual economy that we have studied in the text. In the other extreme with $\xi_1 = 0$, we recover the benchmark model.

Figure E.2 shows the impulse responses of a few macro variables following an expansionary monetary policy shock under different values of ξ_1 . The figure shows that weakening the endogenous risk-weighting channel would mitigate credit misallocations and enhance the stimulus effects of an expansionary monetary policy.

FIGURE E.2. Transition dynamics following an expansionary monetary policy shock: Benchmark model vs. counterfactuals



Notes: This figure shows the dynamic responses to an expansionary monetary policy shock for different scenarios. The risk-weighting function takes the form of $h(\omega_t) = \xi\omega_t^\chi + \frac{\xi_1}{2}(\omega_t - \omega)^2$. A larger value of ξ_1 indicates a weaker risk-weighting channel. The vertical axes show percentage deviations from the initial steady state (e.g., 0.01 corresponds to 1%). The horizontal axes show the periods after the impact period of the shock. The solid lines denote the responses in the benchmark model and the dashed lines are those in the counterfactual case with weaker risk-weighting channel.

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