Online Appendix for "Bank Risk-Taking, Credit Allocation, and Monetary Policy Transmission: Evidence from China"

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A. Stability of credit ratings

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

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

Year	$Rating_t = Rating_{t-1}$	$Rating_t \neq Rating_{t-1}$
2009	5,677	3
2010	6,565	2
2011	8,046	4
2012	9,427	4
2013	9,621	2
2014	8,940	1
2015	8,029	3
2016	6,932	2
2017	6,105	0

B. Further robustness checks

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

Clustering standard errors by firms or firms and branches. In our baseline regressions, we cluster the standard errors at the branch level. In our sample, although a firm's credit rating rarely changes over time, there are repeated observations within each firm. For this reason, we consider two alternative versions of the main regressions reported in Table 4, one with clustering at the firm level and the other with two-way clustering at the branch and firm level. Table B.1 shows that the main results are robust.

Controlling for more loan demand factors. To further control for potential effects of loan demand factors, we add more control variables in the baseline regression. Table B.2 shows the estimation results with successively more stringent controls of demand factors. Column (1) shows the baseline regression that includes firm location fixed effects. Column (2) includes firm location $\times$ year-quarter fixed effects. Column (3) includes industry $\times$ firm location$\times$ year-quarter fixed effects. Column (4) includes firm size $\times$

Table B.1. Effects of monetary policy on bank risk-taking under capital regulations: Alternative clustering

	(1)	(2)	(3)	(4)	(5)	(6)
DV: *HighR*	Full Sample	Full Sample	Excluding SOEs	Full Sample	Full Sample	Excluding SOEs
$RiskH_j \times MP_t \times Post_y$	0.836**	0.848**	0.831***	0.836**	0.848**	0.831**
	(0.335)	(0.332)	(0.315)	(0.381)	(0.376)	(0.357)
$RiskH_j \times MP_t$	-0.661**	-0.679**	-0.684**	-0.661**	-0.679**	-0.684**
	(0.268)	(0.270)	(0.274)	(0.316)	(0.315)	(0.307)
$RiskH_j \times Post_y$	0.00779**	0.00665*	0.00607*	0.00779	0.00665	0.00607
	(0.00395)	(0.00370)	(0.00332)	(0.00477)	(0.00450)	(0.00443)
Branch FE	yes	yes	yes	yes	yes	yes
Year-quater FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Firm location FE	no	yes	yes	no	yes	yes
Initial controls × year FE	yes	yes	yes	yes	yes	yes
Observations	206,738	206,738	197,661	206,738	206,738	197,661
R^2	0.199	0.230	0.204	0.199	0.230	0.204

Notes: This table reports the estimation results in the baseline model with alternative clustering standard errors. $HighR$ is a dummy variable that is equal to 1 if the rating of the loan is AA+ or AAA and zero otherwise. The monetary policy shock (MP_t) is constructed using the approach in Chen et al. (2018). Column (1), (2), (4), and (5) report the regressions using the full sample, while Column (3) and (6) report the regressions using the sample that excludes SOEs. Columns (1) and (4) include controls for branch fixed effects, industry fixed effects, year-quarter fixed effects, and average firm characteristics (including size, age, leverage, tangible asset ratio, and ROA) in the years before 2013 (i.e., initial controls) interacted with the year fixed effects. Columns (2), (3), (5), and (6) include additional controls for firm location (province) fixed effects. The numbers in parentheses indicate robust standard errors. In Columns (1), (2), and (3), the standard errors are clustered at the firm level. In Columns (4), (5), and (6), they are double-clustered at the branch and firm level. The statistical significance levels are indicated by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. The data sample ranges from 2008:Q1 to 2017:Q4.

industry × firm location × year-quarter fixed effects. In each case, we obtain a positive and significant estimate of the coefficients of the triple interaction term $RiskH_j \times MP_t \times Post_y$. Thus, the baseline results are robust to including these demand controls.

Table B.2. Effects of monetary policy on bank risk-taking under capital regulations: Additinoal controls for demand factors

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

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

Measuring monetary policy shocks based on an interest rate rule. In the baseline empirical model, we use a quantity-based measure of monetary policy shocks. In recent years, monetary policy has gradually shifted toward market-based policy, with interest rates used as a policy instrument (Fernald et al., 2014).[1] To check the robustness

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

of our results, We estimate the baseline empirical specification (23), with the monetary policy shock measured by the Taylor rule residuals estimated from the Taylor-rule specification

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

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

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

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

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

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

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

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

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

	(1)
	$HighR$
$RiskH_j \times MP_t \times Post_y$	1.08**
	(0.507)
$RiskH_j \times Post_y$	0.00765*
	(0.00420)
$RiskH_j \times MP_t$	-0.324
	(0.551)
$RiskH_j \times MP_t \times LoanRateGap_{t-1}$	-5.14
	(6.48)
$RiskH_j \times LoanRateGap_{t-1}$	-0.00477
	(0.0332)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial controls × year FE	yes
Observations	193,263
R^2	0.218

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

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

Effects of deleveraging policy: A placebo test. The Chinese government responded to the 2008-09 global financial crisis by implementing a large-scale fiscal stimulus (equivalent to about 12% of GDP). The fiscal stimulus helped cushion the downturn during the crisis period, but it has also led to a surge in leverage and over-investment, particularly in those sectors with a high share of SOEs (Cong et al., 2019). In December 2015, the Chinese government implemented a deleveraging policy, aiming to reduce the leverage in the over-capacity industries. It is possible that the deleveraging policy might have played a role in driving the observed relation between bank risk-taking and monetary policy shocks. To examine this possibility, we conduct a placebo test using China's deleveraging policy. We define a dummy variable, $DeLev_y$, which is equal to one if the year is 2016 or after, and zero otherwise. In the placebo test, we estimate the baseline empirical model (23), replacing the variable $Post_y$ in the baseline model with $DeLev_y$. Table B.5 shows the estimation results. Unlike the banking regulation policy changes under Basel III, the deleveraging policy did not change the bank risk-taking behaviors following monetary policy shocks.

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

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

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

	(1)
	$HighR$
$RiskH_j \times MP_t \times Delev_y$	-0.956
	(1.03)
$RiskH_j \times Delev_y$	0.00156
	(0.00542)
$RiskH_j \times MP_t$	-0.314
	(0.201)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial control × year FE	yes
R^2	0.230
Observations	206,738

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

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

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

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

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

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

The first control variable that we include is the interaction between bank branches' initial profits (denoted by $InitProfit_j$) and the year fixed effects, where the initial profit of branch j is measured by its net interest income in the first year when the branch is observed in our sample. Including this control helps rule out the possibility that the banking regulation may change a branch's lending behavior through affecting its profit.[2]

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

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

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

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

To provide a theoretical underpinning for this alternative identification approach, we extend the baseline theoretical model to incorporate local banking competition in Section F. The model predicts that, following an easing of monetary policy, a bank branch facing more local competition would raise leverage more aggressively and, under the

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

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

	(1) $HighR_{i,j,t}$	(2) $HighR_{i,j,t}$
$RiskH_j \times MP_t \times Post_y$	0.850**	0.848**
	(0.377)	(0.376)
$RiskH_j \times Post_y$	0.00648	0.00637
	(0.00437)	(0.00436)
$RiskH_j \times MP_t$	-0.679**	-0.678**
	(0.315)	(0.314)
$InitProfit_j$ × year FE	yes	yes
$InitSOE_j$ × year FE	no	yes
Branch FE	yes	yes
Year-quarter FE	yes	yes
Industry FE	yes	yes
Firm location FE	yes	yes
Initial controls × year FE	yes	yes
Observations	206,738	206,738
R^2	0.230	0.230

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

CAR constraints, it would also reduce risk-taking more aggressively. Increasing the risk-weighting sensitivity would further amplify those effects.[3]

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

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

	(1) $HighR_{i,j,t}$
$RiskH2_j \times MP_t \times Post_y$	0.261**
	(0.131)
$RiskH2_j \times Post_y$	0.00273
	(0.00194)
$RiskH2_j \times MP_t$	-0.276**
	(0.107)
Branch FE	yes
Year-quarter FE	yes
Industry FE	yes
Firm location FE	yes
Initial controls × year FE	yes
Observations	206,738
R^2	0.230

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

In our regression, we replace the risk-history indicator ($RiskH_j$) with an indicator of local market competition, which is measured by (the logarithm of) the number of subbranches of other commercial banks within a 5-kilometer radius around a given subbranch

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

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

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

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

k of the bank in our sample (denoted as $LocalComp_k$). The presence of a larger number of competing subbranches in the same vicinity (i.e., a larger value of $LocalComp_k$) indicates more intense local competition facing the subbranch k.[4]

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

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

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

Credit ratings and SOE loan share. Table C.1 shows the SOE shares of loans with different credit ratings. SOE loans account for a large share of highly rated loans. In terms of the number of loans, over 20% of the highly rated loans (AA+ or AAA) were extended to SOE firms. In terms of the amount of loans, over 55% of the highly rated loans were extended to SOEs.

Table C.1. Credit ratings and SOE loan share

Credit Rating	Number	SOE Share	Amount	SOE Share
AAA	4280	20.4%	223354	60.5%
AA+	6424	30.8%	294034	55.1%
AA	21357	21.7%	492613	52.4%
AA-	49473	7.9%	604108	31.6%
A+	50301	4.4%	372371	21.5%
A	24712	8.3%	236982	27.2%
A-	14803	2.7%	101295	14.4%
BBB+	13655	1.5%	83454	7.9%
BBB	9437	2.3%	64933	22%
BBB-	4779	0.8%	34362	2.4%
BB	9143	6.9%	90197	21.4%
B	55849	1.6%	407239	4.8%

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

MPK dispersion as a measure of capital misallocation. In the literature, resource misallocations are often measured by the dispersion of marginal product of capital (MPK) [e.g., Hsieh and Klenow (2009)]. We follow the literature and use the MPK dispersion to measure capital misallocation. Since the firm-level characteristics in the ASIF database

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

are not available after 2013, we construct the dispersion of MPK and also of marginal product of labor (MPL) within each province using the data from publicly listed firms.

Table C.2. Bank risk-taking and resource misallocation: MPK dispersion

	(1) MPK dispersion OLS	(2) MPL dispersion OLS
$RiskH_p \times MP_y \times Post_y$	9.332*	7.448
	(4.917)	(4.779)
$RiskH_p \times Post_y$	-0.054	-0.078
	(0.058)	(0.056)
$RiskH_p \times MP_y$	-7.971**	-5.004
	(4.044)	(3.930)
Province FE	yes	yes
Year FE	yes	yes
R^2	0.514	0.495
Observations	330	330

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

Table C.2 reports the estimation results. The estimated coefficient of the triple interaction term $RiskH_p \times MP_y \times Post_y$ in Column (1) is positive and significant, suggesting that, after the implementation of Basel III capital regulations, provinces with higher exposures to risky bank branches experienced larger increases in capital misallocation (measured by the MPK dispersion) in response to an expansionary monetary policy shock. In comparison, as Column (2) shows, the effects of the regulatory and monetary policy changes on the MPL dispersion are insignificant, suggesting that those policy changes are important mostly for the capital misallocations.

D. Exogeneity tests of the monetary policy shock

We test the exogeneity of our measure of monetary policy shocks following the same approach as in Chen et al. (2018), with the sample extended to 2017:Q4 (from their 2016:Q2). We find that the measure is orthogonal to other quantity-based policy instruments such as the required reserve ratio (RRR), and price-based policy instruments (targets) such as Repo and SHIBOR, suggesting that it is exogenous to the state of the economy. Table D.1 reports the detailed results.

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

Table D.1. Endogenous vs. exogenous components in the M2 growth rule

Components in MP	(1) Endo MP	(2) MPShock	(3) Endo MP	(4) MPShock	(5) Endo MP	(6) MPShock	(7) Endo MP	(8) MPShock	(9) Endo MP	(10) MPShock	(11) Endo MP	(12) MPShock	(13) Endo MP	(14) MPShock
RRR	-0.272***	-0.0157												
	(0.0805)	(0.0680)												
DR1			-0.893***	-0.227										
			(0.165)	(0.158)										
DR7					-0.756***	-0.180								
					(0.131)	(0.130)								
DR30							-0.585***	-0.157						
							(0.0969)	(0.0972)						
shibor1									-0.888***	-0.222				
									(0.168)	(0.160)				
shibor7											-0.686***	-0.144		
											(0.142)	(0.132)		
shibor30													-0.572***	-0.137
													(0.104)	(0.101)
Constant	0.0830***	0.00299	0.0561***	0.00567	0.0575***	0.00566	0.0563***	0.00603	0.0558***	0.00550	0.0548***	0.00445	0.0553***	0.00515
	(0.0144)	(0.0122)	(0.00417)	(0.00401)	(0.00417)	(0.00413)	(0.00380)	(0.00381)	(0.00422)	(0.00401)	(0.00440)	(0.00408)	(0.00398)	(0.00386)
Observations	40	40	40	40	40	40	40	40	40	40	40	40	40	40
R-squared	0.231	0.001	0.436	0.052	0.467	0.048	0.489	0.064	0.423	0.048	0.380	0.031	0.442	0.046

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

E. Proofs

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

Lemma 1 and the Proof.

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

$$\frac{\partial \sigma}{\partial \psi} < 0, \quad \frac{\partial \sigma}{\partial \rho} < 0. \tag{E.1}$$

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

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

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

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

$$\begin{aligned}
\frac{\partial V/e}{\partial \lambda} &= E\left[R(\sigma)\right] - r + \int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))}\left(R^*\left(\lambda(\sigma)\right) - R\right)d\mathbf{F}(R) \\
&+ \lambda\frac{\partial}{\partial \lambda}\left[\int_{\underline{R}(\sigma)}^{R^*(\lambda(\sigma))}\left(R^*\left(\lambda(\sigma)\right) - R\right)d\mathbf{F}(R)\right] \\
&= \left(\phi_1 - \phi_2\sigma\right)\sigma - r + \frac{1}{2\sigma}\left(R^* - \underline{R}\right)^2 + \frac{r}{\lambda\sigma}\left(R^* - \underline{R}\right) \\
&= \frac{\left(\bar{R} - R^*\right)}{\sigma}\left(\frac{\bar{R} - R^*}{2} - \frac{r}{\lambda}\right) > 0
\end{aligned}\tag{E.3}$$

Substitute (E.2)(E.3) into the first-order condition, we have the optimizing condition (16), which can be further written as

$$g(\sigma) \equiv \frac{\upsilon(\sigma)}{2\left[\left(\phi_1 - \phi_2\sigma + \frac{1}{2}\right)\sigma - r\left(1 - \psi\sigma^\rho\right)\right]} = 0, \tag{E.4}$$

where

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

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

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

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

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

$$\frac{\partial \upsilon(\sigma)}{\partial \sigma} \equiv \upsilon_{\sigma} = -2(3-\rho)\phi_2\sigma + (1-\rho)\left(\phi_1 + \frac{1}{2}\right) - (1-\rho)\rho r\psi\sigma^{\rho-1}. \tag{E.5}$$

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

$$\upsilon_{\sigma} \leq -(1-\rho)\left(\phi_1 + \frac{1}{2}\right) - (1-\rho)\rho r\psi\sigma^{\rho-1} < 0. \tag{E.6}$$

We also have

$$\upsilon(\hat{\sigma}) = (1+\rho)r - (1-\rho)r\psi\hat{\sigma}^{\rho} > 2\rho r > 0, \tag{E.7}$$

and

$$\begin{aligned} \upsilon(\bar{\sigma}) &= -(3-\rho)\phi_2\bar{\sigma}^2 + (1-\rho)\left(\phi_1 + \frac{1}{2}\right)\bar{\sigma} + (1+\rho)r - (1-\rho)r\psi\bar{\sigma}^{\rho} \\ &= -\rho\left[\bar{R}(\sigma) - r\right] - (1-\rho)r\psi\bar{\sigma}^{\rho} < 0. \end{aligned} \tag{E.8}$$

The second line for $\upsilon(\bar{\sigma})$ is obtained by using the definition of $\bar{\sigma}$, the optimal choice of an unconstrained bank, i.e. $3\phi_2\bar{\sigma}^2 = \left(\phi_1 + \frac{1}{2}\right)\bar{\sigma} + r$. The intermediate value theorem implies that there exists a unique $\sigma \in (0, \bar{\sigma})$ that maximizes the bank's expected profit (i.e., Eq. (E.4) holds).

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

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

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

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

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

□

Proof of Proposition 1.

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

$$\frac{\mathrm{d}\sigma}{\mathrm{d}r} = -\frac{\upsilon_r}{\upsilon_\sigma} = -\frac{(1+\rho) - (1-\rho)\,\psi\sigma^\rho}{\upsilon_\sigma}, \tag{E.9}$$

where υ_σ is given by (E.6). The second equality is from the definition of υ_r. Notice that under the binding CAR constraint, we have $\lambda = \frac{1}{\psi\sigma^\rho} > 1$ and $\upsilon_\sigma < 0$, therefore $(1+\rho) - (1-\rho)\frac{\sigma^\rho}{\psi} > 0$ implying $\frac{\mathrm{d}\sigma}{\mathrm{d}r} > 0$. Moreover, from the CAR constraint we have

$$\frac{\mathrm{d}\lambda}{\mathrm{d}r} = -\frac{\rho}{\psi\sigma^{\rho-1}}\frac{\mathrm{d}\sigma}{\mathrm{d}r} < 0. \tag{E.10}$$

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

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

□

Proof of Proposition 2.

Proof. Taking second-order derivations, we have

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

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

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

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

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

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

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

It is easy to show that

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

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

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

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

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

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

Substitute into Ω, we have

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

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

In conclusion, we obtain

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

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

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

Proof. Taking second-order derivations, we have

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

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

$$\frac{\partial^2\sigma}{\partial r\partial\psi} = -\frac{1-\rho}{\upsilon_\sigma^3}\sigma^\rho\Psi, \tag{E.11}$$

where

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

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

$$\Psi = -\,(3-\rho)\,\phi_2\sigma\left[(3-\rho)\,\phi_2\sigma + \frac{\rho\,(1+\rho)\,r}{\sigma}\right] - (1+\rho)\,\frac{r}{\sigma}\left(1-\frac{1-\rho}{1+\rho}\psi\sigma^\rho\right)\Xi, \tag{E.12}$$

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

$$\Xi > (3-\rho)\,\phi_2\,(\rho+1)\,\sigma - (1-\rho)\,(1+\rho)\left(\phi_1+\frac{1}{2}\right) > 0, \tag{E.13}$$

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

Proof of Proposition 3.

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

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

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

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

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

Proof of Proposition 4.

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

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

It is easy to show that

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

and

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

Therefore, we obtain

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

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

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

and

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

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

$$\frac{\partial\sigma}{\partial r}|_{\rho=0} = \frac{1-\psi}{\sqrt{\left(\phi_1 + \frac{1}{2}\Delta\right)^2 + 12r(1-\psi)\phi_2}} > 0., \tag{E.14}$$

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

$$\frac{\partial\sigma}{\partial r}|_{\rho=1} = \sqrt{\frac{(1+\rho)}{(3-\rho)\phi_2}}\frac{1}{2\sqrt{r}} = \frac{1}{2\sqrt{r\phi_2}}, \tag{E.15}$$

which is independent of Δ.

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

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

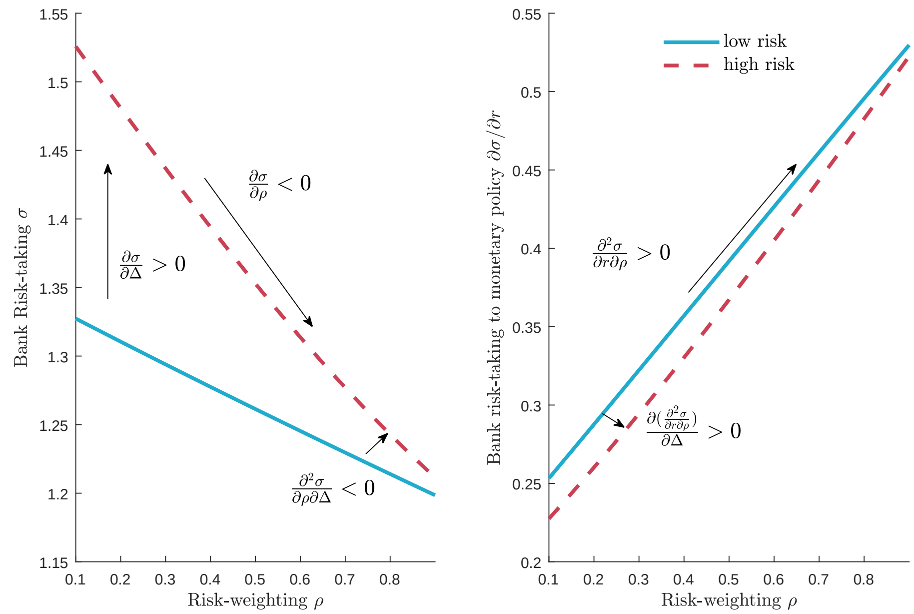
which is increasing in the bank-specific risk Δ. Therefore, $\frac{\partial}{\partial\Delta}\left[\frac{\partial\sigma}{\partial r}|_{\rho=1} - \frac{\partial\sigma}{\partial r}|_{\rho=0}\right] > 0$, and

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

□

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

FIGURE E.1. Bank risk-taking under regulatory changes and monetary policy



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

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

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

F. A model with bank market power

We consider the bank's market power in the loan market to provide an alternative mechanism for identifying the effects of regulatory changes on the bank's risk-taking.[5] We assume that the payoff for project σ includes two components, $g(K)\,R(\sigma)$. The first part, $g(K) = AK^{\alpha-1}$, is marginal return on aggregate capital. Aggregate capital K is financed by loans from individual banks indexed by i, with the constant-elasticity-of-substitution (CES) aggregation technology

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

which decreases with the competition level of the loan market (N). In a more competitive market, the marginal benefit of risk-taking is lower, discouraging bank risk-taking (σ). This result is formally stated in Proposition F.1.

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

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

Proof. We first show the existence of the bank's optimal project choice σ^*. The first-order condition (F.5) can be written as

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

Second-order derivation is given by,

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

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

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

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

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

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

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

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

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

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

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

In general, the impact of regulatory changes (in particular, changes in the risk-weighting sensitivity ρ) on bank risk-taking depends on the level of banking competition (N). In a regime with a higher level of ρ, the bank's market power (F.6) is more sensitive to the banking competition level (N), leading to a greater reduction in bank risk-taking.

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

To summarize, the effects of raising the risk-weighting sensitivity ρ on risk-taking are amplified by the level of banking competition N. These results are formally stated in Proposition F.2.

Proposition F.2. *Under a higher level of the risk-weighting sensitivity (e.g., when ρ increases from 0 to 1), a bank facing a greater level of banking competition (N) reduces risk-taking (σ) more aggressively, that is,*

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

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

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

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

For second-order derivation,

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

It is easy to show that,

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

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

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

where

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

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

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

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

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

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

□

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