

## Research and Development

# Does Bank Lending Intervention Hamper Firm Innovation? Evidence From the Chinese-style Capacity-Reduction Initiative

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Using the difference-in-differences method, this study investigates the impact of bank lending intervention on firm innovation. We find that bank lending intervention significantly hampers R&D investment of firms in overcapacity industries. Moreover, policy intervention significantly reduces bank lending but increases the firms' trade credit as well as the financing constraints of firms in overcapacity industries. Furthermore, bank lending intervention reduces the efficiency of credit allocation, an outcome which is attributed to its preference for politically connected firms rather than higher-efficiency ones.

### I. Introduction

Capital markets in China are notably inefficient, leading to misallocation of capital resources and the overcapacity of particular industries (Hsieh & Klenow, 2009; Shen & Chen, 2017). Overcapacity refers to an economic phenomenon in which total production capacity is greater than the market demand. To prevent the blind expansion of production scale in overcapacity industries, the Chinese government published an intervention policy for bank credit allocation in 2013. This policy requires commercial banks to rein in the supply of credit but provide credit support for the innovative firms in overcapacity industries. Banks have in general refused to lend to all firms in overcapacity industries, including those firms involved in R&D activities. The key question we explore is: will government policy intervention hamper R&D investment?

Bank credit plays an important role in the R&D activities of firms, and empirical evidence suggests that bank credit is positively correlated with firm innovation (Atanassov, 2016). Especially in developing countries, bank credit facilitates firm innovation by providing financial support as well as helping reduce information asymmetry between the firms and other stakeholders (Bolton et al., 2016; Guney et al., 2017). Although some studies confirm that bank loans create debt pressures for firms (Allen & Gale, 2000), bank credit is generally believed to be the most extensive external financing channel used by firms for innovation, particularly in developing countries with imperfect capital markets (Hall, 2002). Credit intervention policy is a common industrial policy in developing countries; therefore, testing effectiveness in facilitating innovation is important.

This study employs data on 621 Chinese listed firms covering the sample 2009 to 2018 and finds that: (a) bank lending intervention hampers firm innovation in overcapacity industries; and (b) bank lending intervention reduces the efficiency of credit allocation. This work extends the existing literature primarily in two aspects. The first is that we establish that government intervention is inefficient in credit allocation and contradicts the goal of providing financial support for innovative activities. Liu et al. (2019) show that the policy of limiting bank credit in polluting industries would increase financing costs, while they do not consider its impact on the upgrade of the restricted industry. The second is that our study focuses on the effects of

credit intervention policies on restrictive industries and enriches research on industrial policy in developing countries. Industrial policies refer to incentive-based policies or restrictive-based policies for specific industries (Wen & Zhao, 2020). Although several studies focus on the effect of incentive-based industrial policy that promotes industrial expansion and development (Bose et al., 2019; Wen & Zhao, 2020), limited studies examine the economic effects of restrictive-based industrial policy that prevents industrial expansion.

The remainder of this paper proceeds as follows. Section II introduces the institutional background. Section III provides the research methodologies and data. Section IV presents the empirical results. Section V concludes this work.

### II. Chinese-style capacity-reduction initiative

Although it occasionally occurs in the market economy, the problem of overcapacity in many industries has threatened the sustainable development of China's economy since 2008 (Yang et al., 2019). China issued a package deal to reduce capacity in 2009, but it was not until 2013 that China intervened in credit allocation for overcapacity industries through the document "*Guidelines for solving the problem of serious overcapacity*" by the Chinese State Council.

This policy requires commercial banks to control credit supply in overcapacity industries while providing credit support to innovative firms in these industries. However, monitoring the use of firm loans is difficult. Meanwhile, commercial banks intend to lend to firms in high-profit industries rather than in overcapacity industries. In response to the policy, commercial banks explicitly require their branches to reduce all loans to overcapacity industries. [Figure 1](#) describes the bank lending trends of listed firms in these industries from 2009 to 2018. Note that bank loans to those firms have declined sharply since the implementation of the intervention policy ([Figure 1](#)).

### III. Model and data

#### A. Difference-in-differences method

To avoid the effect of endogeneity on the estimated results, this study uses the difference-in-differences (DID) method to empirically identify the causal relationship be-

tween credit intervention and firm innovation. We divide firms into treatment and control groups on the basis of credit dependence. In particular, we calculate the variables of long-term loans, bank loans (long-term loans plus short-term loans), and cash received from borrowings and then split the sample into two groups according to the 2013 data, when the policy was implemented. We set the group dummy  $Treat_i = 1$  if the growth rate of firm  $i$  is smaller than the average and  $Treat_i = 0$  otherwise. Furthermore, we set a time dummy variable  $After_t = 1$  if  $t \geq 2013$  and  $After_t = 0$  otherwise. The model is represented as follows:

$$RD_{it} = \alpha_i + \beta Treat_i \times After_t + \Theta Control_{it} + \lambda_t + \varepsilon_{it} \quad (1)$$

where  $RD_{it}$  is a dependent variable and pertains to the R&D investment of firm  $i$  in year  $t$ , the interaction term of  $Treat_i \times After_t$  denotes the effect of bank lending intervention on firm R&D investment, and  $Control_{it}$  is a vector of control variables; see in Table 1. Finally,  $\alpha_i$  is the firm-fixed effect, and  $\lambda_t$  is the time-fixed effect.

## B. Data and variables

The sample consists of 621 Chinese listed firms in overcapacity industries over the 2009 to 2018 period. According to the industry classification standard of GB/4754-2011, eight industries are defined as been in overcapacity: namely, mining and washing of coal, extraction of petroleum and natural gas, mining and processing of ferrous metal ores, mining and processing of non-ferrous metal ores, smelting and pressing of ferrous metals, smelting and pressing of non-ferrous metals, production and distribution of electric and heat industry, and gas production and supply industry. The data are obtained from the Wind database and the China Stock Market and Accounting Research database.

Compared to R&D output, the lag and uncertainty of R&D are lower. The main dependent variable is R&D investment, defined as *RD intensity* (*RDI*, measured as  $100 \times$  the ratio of R&D expenses to sales) and *RD expenditure* (*RDE*, measured as the logarithm of 1 plus R&D expenses). We also use the variables bank loan (*Loan*), trade credit (*TC*), the Kaplan and Zingales (1997) index of the financing constraint (*KZ*), and political connection (*POL*) as dependent variables.

Following Wang et al. (2017) and Wen and Zhao (2020), we consider the following control variables: *InSize* (calculated by the logarithm of total asset), *InAge* (measured by the logarithm of the survival year), *Human* (measured by the ratio of employees with a bachelor's degree or above), *Tobin's Q* (measured by the ratio of market value to total assets), *Leverage* (the ratio of total debt to total assets), *ROA* (the return on assets), *Fixs* (the ratio of fixed assets to total assets), *SOE* is a dummy variable capturing state-owned firms, *Large* (the percentage of shares owned by the largest shareholder), *Manage* (the ratio of administrative costs to sales), and *InTFP*, which is the logarithm of total factor productivity. Table 1 describes each of these variables.

## IV. Empirical result and analysis

### A. Effect of policy intervention on R&D investment

We use *RDI* and *RDE* as dependent variables, and the results are shown in Panels A and B of Table 2. All the coefficients of  $Treat \times After$  are statistically significant (at the 5% level) and negative, thereby indicating that bank lending intervention decreases firm R&D investment. Therefore, the intervention policy contradicts its original goal, which is to promote firm innovation. Despite the request of the government, commercial banks are reluctant to provide loans to

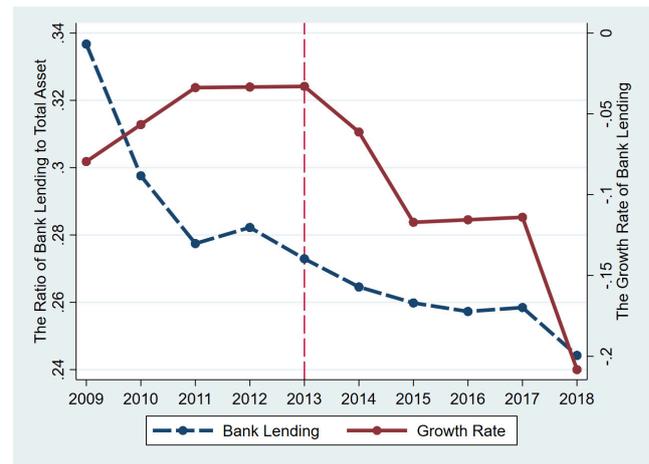


Figure 1. Time trends of bank lending to listed firms in overcapacity industries

Note: This figure plots two sets of data—namely, bank lending, which is scaled by total assets; and the growth rate of bank lending. The virtual line indicates the implementation date.

support R&D activities of these firms. On the one hand, information asymmetry occurs in imperfect financial markets, and all firms will actively apply for limited credit resources (Aboody & Lev, 2000), on the other hand, given the highly uncertain nature of R&D activities, especially for restricted industries, lenders may be exposed to potentially serious risks.

### B. Effect of policy intervention on credit allocation

To investigate the impact of policy intervention on credit allocation, we use *Loan*, *TC*, and *KZ* as dependent variables. We regress these variables on the time dummy *After*, and separately include the interactions of  $After \times SOE$ ,  $After \times POL$ , and  $After \times InTFP$  in the model. The results are shown in Table 3.

Columns (1) to (3) indicate that policy intervention significantly reduces bank lending but increases both trade credit and the financing constraints of firms in overcapacity industries. Thus, the mechanism of bank credit constraint is confirmed, and trade credit is seen as an alternative financing channel when formal financing channels are restricted (Guney et al., 2017). In Columns (4) and (5), the coefficient of  $After \times SOE$  is statistically insignificant and positive, whereas the coefficient of  $After \times POL$  is significant (at the 5% level) and positive. Consistent with Cull et al. (2015), this work verifies that credit allocation favors politically connected firms after the policy intervention, a situation which may be correct for state-owned firms. In Column (6), the coefficient of  $After \times InTFP$  is statistically significant (at the 5% level) and negative, thereby indicating that the policy has seen bank credit channeled to firms with lower productivity. The above result implies that the policy of capacity-reduction initiative reduces the allocation efficiency of credit resources and confirms its causal relationship with firm innovation.

## V. Conclusion

Using the DID method, this study examines the impact of bank lending intervention on firm R&D investment. We use a panel dataset consisting of 621 Chinese A-share listed firms covering the 2009 to 2018 period and divide firms into

**Table 1. Descriptive Statistics**

	Variables	Obs	Mean	SD	Min	Max
Dependent variables	<i>RDI</i>	3250	3.012	2.169	0.040	9.830
	<i>RDE</i>	3250	22.347	1.448	18.733	25.690
Independent variables	<i>lnSize</i>	3250	22.281	1.345	19.311	26.071
	<i>lnAge</i>	3250	2.766	0.349	1.609	3.526
	<i>Human</i>	3250	0.392	0.180	0.051	0.896
	<i>Tobin's Q</i>	3250	1.910	0.904	0.979	4.316
	<i>Leverage</i>	3250	0.433	0.206	0.054	1.033
	<i>ROA</i>	3250	0.038	0.050	-0.149	0.184
	<i>Fixs</i>	3250	0.283	0.164	0.025	0.786
	<i>SOE</i>	3250	0.409	0.492	0.000	1.000
	<i>Large</i>	3250	36.637	15.018	8.980	79.380
	<i>lnTFP</i>	3250	0.003	0.272	-0.969	2.129
Other variables	<i>Manage</i>	3250	0.083	0.053	0.008	0.391
	<i>Loan</i>	3160	0.226	0.192	0.000	0.861
	<i>KZ</i>	3250	-0.472	4.516	-13.384	6.324
	<i>TC</i>	3084	0.132	0.086	0.007	0.426
	<i>POL</i>	2751	0.569	0.495	0.000	1.000

This table provides selected descriptive statistics of all variables used in the regression model. Four statistics of importance are mean, standard deviation (SD), minimum (Min.) and maximum (Max.).

treatment and control groups according to their credit dependence. The results show that bank lending intervention has significantly decreased firm R&D investment in overcapacity industries by reducing the bank credit supply and increasing financing constraints. Furthermore, the bank lending intervention has reduced the efficiency of credit allocation because of its preference for politically connected firms rather than higher-efficiency ones. The empirical results suggest that the intervention policy is inefficient in terms of credit allocation and contradicts its goal of providing financing support for innovation activities in overcapacity industries. Therefore, policymakers should consider the impact of imperfect markets on the effect of policy allocation of resources when formulating industrial policies.

### Declaration of Interest

The authors declare that they have no conflict of interest.

Table 2. Effect of bank lending intervention on R&amp;D investment

Variables	Panel A: Results based on <i>RDI</i>			Panel B: Results based on <i>RDE</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treat</i> × <i>After</i>	-0.2797*** (-3.95)	-0.3694*** (-5.64)	-0.2329*** (-3.52)	-0.2027*** (-4.08)	-0.2514*** (-5.96)	-0.1019** (-2.41)
<i>Human</i>	2.4560*** (12.80)	2.4280*** (12.69)	2.4774*** (12.90)	0.4727*** (4.25)	0.4550*** (4.11)	0.4911*** (4.39)
<i>InAge</i>	-0.6629*** (-6.77)	-0.6341*** (-6.52)	-0.6510*** (-6.61)	-0.2665*** (-4.40)	-0.2476*** (-4.14)	-0.2661*** (-4.38)
<i>InSize</i>	-0.0615* (-1.66)	-0.0787** (-2.16)	-0.0833** (-2.27)	0.7797*** (30.57)	0.7671*** (30.42)	0.7647*** (30.12)
<i>Tobin's Q</i>	-0.0128 (-0.27)	-0.0169 (-0.36)	-0.0100 (-0.21)	-0.0128 (-0.49)	-0.0152 (-0.59)	-0.0094 (-0.36)
<i>Leverage</i>	-0.8444*** (-4.22)	-0.8130*** (-4.07)	-0.8556*** (-4.28)	-0.1685 (-1.23)	-0.1493 (-1.09)	-0.1877 (-1.37)
<i>ROA</i>	3.7616*** (4.91)	3.7835*** (4.93)	3.7689*** (4.87)	3.9793*** (7.93)	4.0004*** (7.99)	4.0227*** (7.95)
<i>Fixs</i>	-0.3900* (-1.75)	-0.4606** (-2.09)	-0.4985** (-2.26)	-0.0439 (-0.25)	-0.0968 (-0.55)	-0.1228 (-0.70)
<i>SOE</i>	-0.2735*** (-3.90)	-0.2777*** (-3.98)	-0.2833*** (-4.04)	-0.1008** (-2.01)	-0.1048** (-2.11)	-0.1127** (-2.25)
<i>Large</i>	-0.0049** (-2.36)	-0.0051** (-2.50)	-0.0049** (-2.36)	-0.0005 (-0.37)	-0.0007 (-0.50)	-0.0004 (-0.32)
<i>InTFP</i>	-0.2761** (-2.39)	-0.3036*** (-2.66)	-0.2839** (-2.45)	0.0217 (0.26)	0.0026 (0.03)	0.0162 (0.19)
<i>Manage</i>	15.3335*** (14.98)	15.3598*** (15.03)	15.1626*** (14.74)	-0.4910 (-1.11)	-0.4762 (-1.08)	-0.5864 (-1.30)
<i>Cons</i>	3.6022*** (4.06)	3.9081*** (4.45)	4.0371*** (4.58)	4.4660*** (7.36)	4.6947*** (7.80)	4.7897*** (7.92)
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Adjust R<sup>2</sup></i>	0.5114	0.5137	0.5109	0.5066	0.5086	0.5046
<i>Observations</i>	3250	3250	3250	3250	3250	3250

This table reports results from the regression-based on the DID model. Figures in parentheses indicate *t*-statistics testing the null hypothesis that the slope coefficients are zero. Robust standard errors are used for calculating the *t*-statistics. Finally, \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Effect of policy intervention on credit allocation

Variables	(1)Loan	(2)TC	(3)KZ	(4)Loan	(5)Loan	(6)Loan
<i>After</i>	-0.0085*	0.0215***	1.0632***	-0.0123*	-0.0147**	-0.0086*
	(-1.72)	(9.64)	(12.52)	(-1.91)	(-2.36)	(-1.75)
<i>After</i> × <i>SOE</i>				0.0075		
				(0.86)		
<i>After</i> × <i>POL</i>					0.0139**	
					(2.23)	
<i>After</i> × <i>lnTFP</i>						-0.0368**
						(-2.27)
<i>Control variable</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	No	No	No	Yes	Yes	Yes
<i>Adjust R<sup>2</sup></i>	0.4152	0.4094	0.6801	0.4152	0.4184	0.4158
<i>Observations</i>	5098	4977	5015	5098	4550	5098

This table reports regression results of credit allocation on the policy intervention. The regression data used in this table includes those enterprises that do not report R&D investment. The variables in first row refer to the explanatory variables. We have also employed control variables, individual fixed effects, and time fixed effects. Figures in parentheses indicate *t*-statistics testing the null hypothesis that the slope coefficients are zero. Robust standard errors are used for calculating the *t*-statistics. Finally, \*\*\*, \*\*, and \* represent statistical significance at the 1%, 5%, and 10% levels, respectively.



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