Credit Allocation under Economic Stimulus: Evidence from China

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Abstract

We study credit allocation across firms in a dynamic economy with financial frictions. In normal times, growth is driven by gradual reallocation of resources from low to high productivity firms. Recessions can slow down or even reverse this process of reallocation, due to implicit bail-out of low-productivity state-controlled firms. This effect is amplified by stimulus programs implemented in response to recessions. We test the empirical predictions of the model using China’s economic stimulus plan introduced in 2008, which triggered a large policy-driven credit expansion. Using private firm-level data we show evidence consistent with reallocation reversal. That is, differently from the pre-stimulus years, new credit was allocated relatively more towards state-owned, low-productivity firms than to privately-owned, high-productivity firms.

EFM Codes: 570, 540

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1 Introduction

A large literature in economics has documented that reallocating resources from low to high productivity firms is an important source of economic growth. In the absence of frictions, this process is fast and resources are allocated to their most productive users. In most countries, however, this process is plagued by frictions, such as the influence of different levels of government on capital and labor markets. Examples of this influence include: directed lending by government-controlled banks, government subsidies to certain industries, or preferential access to external finance by state-sponsored firms. In these instances, inefficient firms are artificially kept alive, or even rewarded with larger market shares, often at the expense of private, more productive firms. This problem becomes particularly important during recessions, when – to contain unemployment and sustain aggregate demand – central and local governments take a larger role in allocating resources relative to normal times. This has been the case, for example, when governments in both developed and developing countries introduced economic stimulus programs in response to the Great Recession. Despite being praised by international organizations and economists alike, there is scarce empirical evidence on the unintended consequences of these programs in terms of resource allocation across firms, especially in developing economies that traditionally suffer from severe financial frictions.

In this paper we study the dynamics of credit allocation across firms in China before and after the introduction of the 2008 stimulus plan. We start by showing a set of stylized facts. First, we document that during the “boom years” between 2000 and 2008, private firms in China were experiencing a relatively higher increase in borrowing relative to state-owned firms. This is consistent with the gradual reallocation of credit from low to high productivity firms described in Song, Storesletten, and Zilibotti (2011) as an important part of China economic transformation in the early 2000s. Second, we document that this process of efficient reallocation reversed after the introduction of China’s stimulus plan at the end of 2008. The stimulus package prominently features a 4-trillion RMB investment plan as a response to the Great Recession, but accompanying that is a large credit expansion involving increasing bank credit supply to the real economy.

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1Buera and Shin (2013) show how reforms involving retrenchment of government’s intervention in the economy can lead to resource reallocation to high productivity firms and growth acceleration. In their seminal work on the relationship between financial development and growth, King and Levine (1993) show that the percentage of credit allocated to nonfinancial private firms is strongly associated with GDP growth (“A financial system that simply funnels credit to the government or state-owned enterprises may not be evaluating managers, selecting investment projects, pooling risk, and providing financial services to the same degree as financial systems that allocate credit to the private sector”, King and Levine 1993, p.721).

2For example, in 2008, the IMF managing director Dominique Strauss Kahn and the World Bank president Robert Zoellick described China stimulus plan as a stabilizer for the world economy. Nobel laureate Paul Krugman praised the scale of the stimulus plans in South Korea and China when advocating for larger stimulus in the US.
through higher lending quotas and lower reserve requirements for commercial banks.\textsuperscript{3} We document that, despite their lower marginal productivity of capital, between 2009 and 2013, state-owned firms have been experiencing a relatively higher increase in firm borrowing with respect to private firms.

We propose a simple theoretical framework to illustrate how financial frictions can affect credit allocation. Specifically, we model a dynamic economy in which firms are heterogeneous in two dimensions: productivity and state connectedness, both of which affect their ability to access external finance. Private firms are operated by skilled entrepreneurs, have higher productivity, and rely on both private investments and bank loans to grow. On the other hand, state-connected firms are neoclassical, employ regular workers and in equilibrium only borrow from banks. As in Song et al. (2011), a country’s growth thus derives from the reallocation of resources from the latter to the former, and this transition is limited by pledgeability constraints that plague private firms. We augment their framework by explicitly modeling time-varying economic environment and by accounting for implicit government bail-out of state-connected firms. In this economy, recessions slow down the efficient re-allocation of capital from low to high-productivity firms and can potentially reverse the prior trend of factor reallocation. Selective government bail-out endogenously determines the differential interest rates faced by private and state-connected firms, and can lead to reversal even when the pledgeability constraint is only occasionally binding. The intuition is that, during recessions, firms struggle to survive and differential access to external finance becomes more prominent. Finally, we show that credit supply shocks during recessions amplify the probability of a reversal. More broadly, these findings are informative for policy-driven credit expansions in economies characterized by preferential access to finance for government connected firms.

In the data, the timing of the reversal in credit allocation is suggestive of this effect being driven by China stimulus plan, consistently with our model. However, we can not rule out other explanations. In particular, the main identification challenge is to isolate changes in firm borrowing that are solely driven by credit supply shocks rather than by credit demand or investment opportunities faced by firms. In the spirit of Bartik (1991), we therefore propose a measure of firm exposure to the credit supply shock generated by the stimulus plan. First, we exploit the fact that different banks experienced different increases in corporate lending during the stimulus years. Second, we couple data on corporate lending at bank-level with balance sheet information at firm-level from the Annual Industrial Survey, a comprehensive survey that covers all medium to large manufacturing firms in China between 1998 and 2013. As we do not directly observe bank-firm lending relationships, our measure of exposure exploits differences in the geographical location of the branch network of Chinese banks. In particular, we exploit the fact that lending

\textsuperscript{3}According to total social financing data from People’s Bank of China, new loans expanded by 9.59 trillion RMB in 2009, almost doubling that a year ago.
market shares of Chinese banks vary substantially across cities. Therefore, we use data on bank branch addresses to construct a measure of initial exposure of firms located in each city to the overall lending of each bank. Finally, to capture the effect of local demand shocks as well as sector specific demand shocks affecting bank lending, we introduce in the equation to be estimated both province and industry fixed effects interacted with time fixed effects. The rationale behind this identification strategy is to compare firms that are exposed to the same province-level and sector-specific demand shocks, but that differ in their exposure to changes in total lending by different banks.\footnote{We believe this approach can be useful whenever the traditional Bartik instrument cannot be constructed due to data limitations. It is also useful when data limit reserchers to use within borrower estimation coupled with quasi-exogenous liquidity shocks to disentangle credit supply from credit demand (for example, Khwaja and Mian (2008), Paravisini (2008), Chernenko and Sunderam (2014), and Schnabl (2012)).}

Using this measure of exposure to bank credit supply shocks we study credit allocation across different types of firms and its real effects during the stimulus years. Our results are consistent with the theory: during the stimulus years of 2009 and 2010, bank credit was allocated disproportionately more towards state-owned firms. The magnitude of our estimates indicate that, for a 1 standard deviation increase in bank credit supply exposure, state-owned firms experienced a 10-times larger increase in long term debt with respect to private firms. Consistently with this finding, we show that firms with lower initial marginal product of capital experienced a relatively larger increase in borrowing than firms with higher initial marginal product of capital. This result suggests an increase in the misallocation of credit supplied by the banking sector to the real economy during the stimulus years. Finally, we test for real effects and find that low marginal product of capital firms experienced also a relatively larger increase in capital investment. This finding suggests an increase in the misallocation of physical capital during the stimulus years.

Related literature

A large literature in finance and development studies misallocation and the process of factor reallocation across firms in developing countries transitioning to market economies. Early contributions include Lewis (1954) on reallocation between rural and urban areas and Ventura (1997) on reallocation between labor-intensive and capital-intensive sectors. Hsieh and Klenow (2009) document severe misallocation in China and India, and estimate that reallocation across manufacturing firms can account for an increase in TFP of 30\% – 50\% in China and 40\% – 60\% in India. Restuccia and Rogerson (2008) propose a theory of how resource allocation across establishments of different productivity contributes to aggregate output. Buera and Shin (2013) show how reforms involving retrenchment of government’s intervention in the economy can lead to resource reallocation from low to high productivity firms and growth acceleration. Song et al. (2011) propose a model where China’s fast economic growth and its concurrent net capital outflow can
both be rationalized by reallocation of capital and labor from less productive but financially integrated firms to more productive but credit rationed firms. The presence of financial frictions in their model partly obstructs the reallocation of capital towards more productive firms, explaining how China experienced a large net foreign surplus despite a high rate of return on domestic investment.\(^5\) Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015) investigate the evolution of capital and labor misallocation and show that, following the introduction of the euro, countries in the South of Europe characterized by less developed financial markets experienced both an increase in capital inflows and an increase in misallocation of resources across manufacturing firms. We study the dynamics of resource misallocation and reallocation under economic stimulus, emphasizing the causal relationship between credit supply shock and inefficient allocation.

Our paper is also related to recent work on China’s credit boom that started with the stimulus program. Two issues that have received growing attention in the last years are the large increase in off-balance sheet borrowing by local government through special financing vehicles and the rise of shadow banking. For example, Huang, Pagano, and Panizza (2016) exploit variation in public debt issuance across Chinese cities to show that debt issuance by local governments had a negative effect on private investment by Chinese firms. Deng, Morck, Wu, and Yeung (2015) argue that China’s economic stimulus mimics the credit channel for monetary policy, but actually entails internal transfers between arms of the government generating an upward pressure on real estate prices.\(^6\) Another aspect that has characterized the recent credit boom in China has been the increase in shadow banking. Hachem and Song (2016) provide a theory of shadow banking in which the government enforces the loan-to-deposit ratio requirement, small banks start offering off-balance-sheet wealth management products, and channel these savings into less regulated Trusts.\(^7\) Chen, He, and Liu (2016) examine how off-balance sheet financial institutions continued to grow after the stimulus, partially by issuing public bonds and continued borrowing from banks and shadow banks. While shadow banking and public bonds have experienced a dramatic growth, bank credit is still dominant in China’s credit market both before or after the introduction of the stimulus plan (see Figure 1 discussed in more details in section 2).

While our paper primarily draws evidence from China, now the world’s second largest economy, the insights could apply more broadly to other forms of credit expansions, liquidity injections, and stimulus programs that aim to provide to stimulate real economic activities, but with unintended consequences due to market frictions. Therefore, this

\(^5\)Empirically, they document a decrease in the share of state-owned firms in industrial output during the last two decades, which traditionally have lower productivity but better access to bank finance than private firms.

\(^6\)On the short term impact of the package, see also: Ouyang and Peng (2015) and Wen and Wu (2014).

\(^7\)Following Hachem and Song (2016) we define shadow banking as both loans by trust companies (trust loans) and entrusted firm-to-firm loans (entrusted loans), but classify bankers’ acceptances as “other”.

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paper also adds to the active research on the impact of monetary policy, asset purchases, or aggregate stimulus on credit supply and on the economy. Prior studies show that policies affect financial institutions’ lending behaviors, which in turn impact borrowing firms (for example, Bernanke, 1983; Stein, 1998; Kashyap and Stein, 2000). Policies that expand credit, boost asset prices, or improves liquidity can have beneficial real effects (for example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Shleifer and Vishny (2010)), but there is limited discussion on their unintended consequences. In that regard, this paper is related to Bleck and Liu (2014) that develops a theory of sectoral misallocation under excessive liquidity injections, and to Chakraborty, Goldstein, and MacKinlay (2016) which studies the crowding-out effect in bank lending. Rather than discussing monetary transmission through asset prices, or emphasizing regional or sectoral misallocation that could be driven by governments’ strategic considerations and promotions, we focus on the dynamics of firm-level misallocation, and empirically test model implications.

The rest of the paper is organized as follows. Section 2 provides the institutional background and highlights the main feature of the Chinese stimulus plan. Section 3 develops a dynamic model that illustrates the allocative effects of credit expansion in an economy with severe financial frictions. Section 4 describes the main data sets used in the empirical analysis, and section 5 discusses the identification strategy. Finally, section 6 presents the main empirical results, and section 7 concludes.

2 Background and Stylized Facts

The second half of 2008 saw the onset of the global recession. China, after almost 30 years of unprecedented growth and with a large exposure to international trade, was expected to face a hard landing. To avert large-scale unemployment and economic slowdown, the Chinese government introduced a larger economic stimulus plan – a combination of fiscal and credit programs collectively known as the “4 Trillion Plan”, which prominently featured spending CNY $4 trillion (US$586 billion) over the following two years (2009 and 2010) on a wide array of national infrastructure and social welfare projects, such as rebuilding communities hit by the Wenchuan Earthquake in May 2008. The program was officially announced on Nov 9, 2008 and, along with an increase in public spending in areas such as affordable housing, transportation, and rural infrastructure, it consisted of a set of provisions aimed at expanding credit by commercial banks.

Unlike deficit-financed stimulus plans in the US and Europe, about two-thirds of
China’s stimulus package was actually funded by bank loans. The central government directly funded only $1.18 trillion CNY using government budget and treasury bonds (0.18 in 2008, 0.5 in 2009, 0.5 in 2010, around 30% of the stimulus program), while the remaining 2.82 billion were financed through borrowing by local governments, corporate bonds, and bank loans. Moreover, at the beginning of 2009 the PBOC and the China Banking Regulatory Commission encouraged the establishment of local government financing vehicles (LGFVs) and other borrowing platforms for the first time, which rely primarily on bank credits. For all these reasons, bank credit expansion under the stimulus was as critical as the directives on investments.

The government traditionally controls bank credit supply with loan quotas, fixed deposit and lending rates and required reserve ratios. The stimulus was therefore primarily introduced as a relaxation of these constraints. First, in the last quarter of 2008, the People Bank of China (or PBoC, the central bank) lowered commercial banks’ reserve requirement ratio from 17.5% to 13.5% for small banks and from 17.5% to 15.5% for large banks. Figure (4) shows the required reserve ratio as well as the actual average reserves for large and small banks. As shown, Chinese banks keep the minimum amount reserves required by the PBoC and, and immediately react to variation in mandatory reserves. Second, the PBoC reduced the base one-year lending rate from 7.47% to 5.31%, and the base deposit rate from 4.14% to 2.25%. Third, the PBoC substantially increased loan quotas of all commercial banks, and explicitly encouraged bank officials to lend up to their new quota levels. In particular, overall lending targets increased from $4.9 trillion CNY in 2008 to almost $10 trillion CNY in 2009.

Figure 1 shows the annual credit flow from the financial system to the real economy according to PBoC data between 2002 and 2015. The annual credit flow is divided into 5 categories: bank loans, equity financing, corporate bonds, and off-balance sheet lending which we label “shadow banking” – this includes trust loans, entrusted loans, and bankers’

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11In this sense, it is important to notice that due to a late start of the modern financial system in China, sources of external finance for firms are limited and banks have traditionally played a dominant role in funding private and public enterprises. The domestic equity market just experienced a historical crash in 2007-08 and was slumbering into what was to become a 7-year-long dormant state. Government and corporate bond market was still underdeveloped.

12http://www.gov.cn/gongbao/content2009/content_1336375.html LGFVs are local government-owned entities that typically use resources from local governments such as land as collateral to obtain loans from banks to finance infrastructure projects. According to a survey by the PBOC, by 2010 the total bank loan taken by local investment platforms constitutes more than 80% of total assets of these platforms. http://news.163.com/special/00012Q9L/difangcaizheng091204.html, http://news.163.com/special/00012Q9L/difangcaizheng091204.html, http://news.163.com/special/00012Q9L/difangcaizheng091204.html

13The loan-to-deposit ratio requirement of 75% was written into law on commercial banks in 1995 and was only lifted in late 2015. Most banks other than the Big Four found it difficult to raise inexpensive deposits sufficient to fund their loan growth while meeting this requirement. Reserve requirement ratio was also limiting banks’ lending capacities. Loan quotas that were in place prior to 1998 and after 2010 constrained the ability of most banks to lend as much as they would otherwise choose to do. For more details and how these encouraged shadow banking, see Elliott, Kroeber, and Qiao (2015).
acceptances – as well as other financing sources. Two important stylized facts emerge from this figure. First, the annual flow of bank lending to the real economy increased from 5 to 11 Trillion CNY (or around 1 Tr USD) between 2008 and 2009. This is consistent with the measures introduced by the PBoC at the end of 2008 described above. Second, despite the significant growth of shadow banking and the bond market, the Chinese financial system is still a bank-dominated financial system.

2.1 Stylized Facts

We start by documenting a set of basic stylized facts in our data. First, we document that manufacturing firms covered in the Annual Industrial Survey display a sharp increase in long term liabilities during the years of the stimulus plan, that is consistent with the increase in bank credit flows to the real economy reported in Figure 1. Figure 3 shows the level and the yearly change in long-term liabilities across firms in the Annual Industrial Survey. To insure comparability over time, we focus exclusively on firms with annual revenues above 20 million CNY (CPI adjusted), for which the survey is effectively a Census between 1998 and 2013. The left graph of Figure 3 reports the sum across firms of the monetary value of long-term liabilities in each year. The right graph reports the year on year difference of this sum. As shown, there is a sharp and positive increase in long term liabilities in both 2009 and 2010. If we were to interpret long term liabilities as composed exclusively by bank debt, Figure 3 suggests that bank credit flow to manufacturing firms was 1.25 Trillion CNY in 2009 and 1.61 Trillion CNY in 2010. The average between 1999 and 2008 was 0.17 Trillion CNY for firms of comparable size. The increases observed in 2009 and 2010 correspond to, respectively, 12% and 19% of the total bank credit flow to the real economy reported for the same years by the Total Social Financing Database of the People’s bank of China (see Figure 1). Notice also how the yearly change in long term liabilities decreases in the years after the stimulus covered in our data (2011 to 2013).

After documenting that our data on manufacturing firms does capture an increase in long-term liabilities that is consistent in timing with the credit supply shock introduced by the stimulus program, we document which types of firms experienced the largest increase in borrowing during the stimulus years. To this end, we estimate the following equation:

\[
\Delta y_{icjt} = \alpha_t + \alpha_c + \alpha_j + \beta C_{icjt-1} + \gamma \log L_{icjt-1} + \varepsilon_{icjt}
\]  

(1)

where the outcome variable is the change in long term liabilities of firm \(i\) between year

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14The data source is the “Total Social Financing” (TSF) dataset of the PBoC. It is important to notice that this dataset does not include government and municipal bonds. Also, data for 2015 does not include loans to local SPV (Special Purpose Vehicles) swapped into municipal bonds by initiative of the Finance Ministry. This implies the total flow for 2015 reported here is likely a lower bound of the actual flow.

15See section 4 for a detailed description of the data sources and variables.
t − 1 and year t (our proxy for new loans) divided by total revenues of firm i in t − 1.\(^{16}\) The subscript c identifies a city, and j a 4-digit sector. The variable \(C_{icjt−1}\) is a pre-determined firm characteristic and captures, depending on the specification, different measures of the ownership status of firm \(i\). We add to this specification year, city and sector fixed effects, as well as the logarithm of number of workers in year \(t − 1\) as a control for firm size. Finally, we divide the sample in different sub-periods between 1998 and 2013 and estimate equation (1) separately for each sub-period. This allows us to estimate equation (1) separately for pre-stimulus, stimulus and post-stimulus years. In addition, it allows us to estimate equation (1) under different government policies towards state-owned firms. Notice that, in each sub-period, we are effectively comparing firms of similar size that are operating in the same city and sector.

Table 2 reports the results of estimating equation (1) using different measures of state ownership. In Panel A we use a dummy equal to 1 if the Government is the controlling shareholder of firm \(i\). In Panel B we use a dummy equal to 1 if either the Government is the controlling shareholder of firm \(i\) or the Government owns 50% or more of the shares of firm \(i\), which is the proxy used to identify state-owned firms proposed by Hsieh and Song (2015).

As shown, state-owned firms experienced, between 2000 and 2008, between 12% and 50% lower levels of new loans as a share of their revenues with respect to privately owned firms. This is consistent with capital being reallocated from low-productivity SOE to high-productivity private firms during the 2000s. The only exception is the change in lending between 1998 and 1999, which we treat separately because it pre-dates the new policy favoring the privatization of SOEs introduced by the Communist Party’s Central Committee in September of 1999.\(^{17}\) Starting from 2009, instead, state-owned firms experienced, on average, between 10 and 15% higher levels of new loans as a share of their revenues. Notice that the positive correlation between state ownership and new loans extends outside the two years of the stimulus plan to the 2011-2013 period. In Figure 7 we plot the estimated coefficients reported in Panel B of Table 2 along with their 95 percent confidence intervals for each sub-period.

The timing of the correlations presented in Table 2 is suggestive of an effect of the stimulus plan on credit allocation between SOE and non-SOE firms. However, it is important at this point to emphasize how the estimates presented in this section cannot be interpreted as directly derived from credit supply shocks, because we cannot separate the effect of the stimulus or other forces affecting credit supply from credit demand forces operating contemporaneously. The paper proceeds as follows. First, in section 3, we present a theoretical framework that rationalizes the stylized facts presented above. Then, in

\(^{16}\) The results are robust to using total assets in year \(t − 1\) as scaling factor. We prefer to scale with total revenues as this is the variable used by the National Statistical Institute to select firms that are surveyed with probability one.

\(^{17}\) For more details see Hsieh and Song (2015).
section 5, we present an identification strategy that aims at disentangling supply from demand forces.

3 The Model

The objective of this section is to develop a simple model that illustrates how financial frictions can affect credit allocation across state-owned and private firms in a dynamic setting. Our model builds on Song et al. (2011), but instead of focusing on the buildup of foreign surplus during economic transition, we focus on credit expansion in a time-varying and uncertain economic environment. We also endogenize interest rates and allow the pledgeability constraint to only occasionally bind.

3.1 Setup and Assumptions

Time is discrete and infinite. There are two types of firms in each period, both requiring capital and labor to operate. A unit measure of state-owned or state-connected enterprises (S firms) operate as standard neo-classical firms and, as discussed in more details later, have better access to banks’ credit because the state acts as a guarantor for the loans they take. Private enterprises (P firms) are started and operated by skilled young entrepreneurs (thus are more productive on average) using capital from private financiers (successful, old entrepreneurs) or banks or both.

The production technology of S and P firms are as follows,

\[
y_{S,t} = k_{S,t}^\alpha (\tilde{A}_{S,t} n_{S,t})^{1-\alpha} \quad y_{P,t} = k_{P,t}^\alpha (\tilde{A}_{P,t} n_{P,t})^{1-\alpha}
\]

where \(y, k, \) and \(n\) are output, capital, and labor, respectively. Capital fully depreciates and firms shut down after each period. \(\tilde{A}_{S,t} = A_t\) with probability \(\mu_t\) (success), and 0 otherwise (failure). Similarly, \(\tilde{A}_{P,t} = \chi A_t\) with probability \(\mu_t\), and 0 otherwise. \(A_t\) is the labor-augmenting technology, and we assume it to be a constant and model the time-varying environment including the economic recession through the changes in \(\mu_t\).

Entrepreneurs, workers, and bankers populate the economy. A measure \(N_t\) of workers work for either P firms or S firms, and get paid the equilibrium wage when the firm is successful, which they consume in each period.\(^{18}\) We set \(N_t\) to be a constant to focus on the labor share dynamics and illustrate key mechanisms.\(^{19}\)

A measure \(M_t\) of skilled entrepreneurs are born in each period and live for two periods,

\(^{18}\)Song et al. (2011) model workers as OLG to explain foreign surplus, but it does not add to our results. For simplicity, we model workers as “hand-to-mouth.”

\(^{19}\)Population growth and demographic changes can be easily incorporated, but are less prominent around the stimulus period and do not add to our economic mechanism.
with preferences parametrized by:

\[ U_t = \frac{(c_{1,t})^{1-\theta} - 1}{1 - \frac{1}{\theta}} + \beta \frac{(c_{2,t+1})^{1-\theta} - 1}{1 - \frac{1}{\theta}} \]

where \( \beta \) is the discount factor, \( \theta \geq 1 \) is the intertemporal elasticity of substitution in consumption \( c \) that ensures private investment (discussed later) to be non-decreasing in the rate of return, \( t \) marks the period in which an entrepreneur is born. We similarly normalize \( M_t = 1 \). In the first period, young entrepreneurs each starts a P firm (with the help from successful old entrepreneurs from the previous period), makes operation decisions, obtains a fraction \( \phi \) of the profit, consumes, and places the remaining profit either in the bank deposits (or directly lending to S firms) which earns weakly less than \( R_S \) in the next period, or a private fund that invests in a diversified portfolio of private enterprises that operate the next period.\(^{20}\) In the next period, if old entrepreneurs have invested in a private fund, they get a fraction \( 1 - \phi \) of each P firm they invest in.

There is a unit measure of risk-neutral intermediaries (banks) each with \( Q_t \) unit of credit supply in period \( t \) that is time-varying. We model credit expansion or contraction as exogenous unexpected shifts to \( Q_t \) that is otherwise stable.\(^{21}\) The credit market is competitive and bankers rationally set lending rates to S and P firms to clear the market.

The state acts as a guarantor for the loans S firms take, which leads to two financial frictions. First, as in Song et al. (2011), P firms can only pledge a fraction \( \eta \) of the firm value for paying off loans and interests to banks. In other words, when a P firm is successful, \( R_{P,t}l_{P,t} \leq \eta \pi_{t}(k_{P,t}, n_{P,t}) \), where \( R_{P,t} \) is the gross interest rate for P firms, \( l_{P,t} \) is the amount of lending, and \( \pi \) is the after-wage revenue. This limited pledgeability friction is absent for S firms because the state can always supply additional assets and collateral.\(^{22}\) Second, when the S firms fail, the state bails them out and pays off the loan with positive probability \( b \). This corresponds to situations in which state-owned banks write off debts of bankrupt SOEs and a government-run committee reorganizes or merges the assets with other SOEs. As such, bankers in expectation get \( R_{S,t}l[\mu_t + (1 - \mu_t)b] \). There thus naturally emerges a dual-track interest rate, \( R_{S,t}l = \delta R_{P,t}l \), that is observed in reality. \( \delta = \frac{\mu}{\mu + (1 - \mu)b} \) captures how much S firms are differentially favored in terms of interest rates or cost of capital (the interest rate friction).

The differential pledgeability constraints and interest rates can be thought as reflecting

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\(^{20}\) We believe that allowing entrepreneurs to share the profit and loss is the major distinction between P and S firms, and captures the historical reforms of State-owned enterprises in China. Alternatively, \( \phi \) could be a bargaining outcome, or determined by an agency friction described in Song et al. (2011): young entrepreneurs run firms owned by old entrepreneurs, need to be paid a management fee high enough that they do not steal part of the profits (old entrepreneurs are good at monitoring but not perfect). For simplicity, we also shut down the choice of young entrepreneurs choosing to be workers, which can be ruled out with further parameter restrictions.

\(^{21}\) In reality, \( Q_t \) is time-varying post-stimulus and the stimulus could have been anticipated. This is not crucial to our results.

\(^{22}\) We can alternatively set \( \eta = 1 \) for S firms and show in equilibrium the constraint does not bind.
several real world frictions commonly observed in emerging economies transitioning to market-based systems but where state influences still linger. For example, loan officers prefer to lend to State-connected or SOEs for several reasons: (1) the government more likely bails them out which prevents loan defaults; (2) SOEs are typically larger which enables bankers to complete lending quota or satisfies their empire-building motives with less effort; (3) bankers have less screening cost and responsibility when lending to SOEs, especially during the stimulus, since they are less to blame in events of default or non-performance. Moreover, loan officers and banks’ incentives are not fully aligned with the intention of the stimulus due to individual career concerns, personal network, and uncontractible effort and unobservable quality. The two frictions in the model adequately capture these phenomena, and are essential drivers for the gradual reallocation of resources between S and P firms.

Notice that $\delta < 1$ does not imply that SOEs do not go bankrupt. What we assume is that if that happens, the government is likely to repay creditors. This matches real life observations in that many insolvent SOEs are being kept alive because creditors (mainly state owned banks) do not initiate bankruptcy proceedings, or the government invokes an escape clause contained in Article 3 of the 1986 trial bankruptcy law. The government also frequently plans reorganization or merger of bankrupt SOEs. Alternative to government bailouts, $\delta$ can also capture bankers’ incentive distortions. For example, the probability that they are to blame for bad loans is lower if they lend to S firms.

We further assume: (1) $[\delta \eta]^{\alpha} \chi^{1-\alpha} < 1$, otherwise the pledgeability constraint never binds for P firms. (2) $[(1-\eta)(1-\phi) - \eta \delta] \chi^{\frac{1-\alpha}{\alpha}} > 1$, to ensure old entrepreneurs invest in the private fund that finances P firms, rather than lending to S firms. This automatically implies $\chi > 1$, which captures the well-documented fact that S firms are typically less efficient than P firms. (3) Young entrepreneurs prefer starting their own firms rather than getting paid as workers. In other words, a business owner or manager gets compensated more than a regular worker.

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23They generally believed that lending to SOEs is safer, and were under pressure from the government to sharply increase lending over a short period of time that was insufficient for careful screening.

24The government typically does not let SOEs go to court, and banks can always track down the government who needs to be responsible for paying off the loan (many SOEs are not limited liabilities, or even when they are, government cares about reputation and social stability enough to pay off the loan), but have difficulties dealing with private entrepreneurs who have limited liabilities.

25According to Steinfeld (2000); Kornai, Maskin, and Roland (2003), the arrangement of having state-directed banks lending to money-losing SOEs is common in command economies that attempted to liberalize. These banks were periodically bailed out themselves when bad loans surfaced, perpetuating the problem of such soft loans.

26We only need there to be sufficient capital in the economy to ensure this. Note that because that the entrepreneurs face the same risk of company failure as workers and as managers, risk aversion does not matter for this decision.
3.2 Dynamic Equilibrium

An S firm maximizes its static profit in each period, taking the interest rate $R_S$ and wage $w$ as given. For notational simplicity, we leave out the time $t$ subscript unless there is ambiguity. Since it gets nothing in the failure state, an S firm solves the following optimization in each period:

$$\Pi_S = \max_{k_S, n_S} k_S^\alpha (An_S)^{1-\alpha} - wn_S - R_S k_S$$

First-order conditions pin down the equilibrium wage:

$$w = (1 - \alpha) \left( \frac{\alpha}{R_S} \right)^{\frac{\alpha}{1-\alpha}} A$$

Now P firms, if successful, pay wage to workers, pay back the loan, and then distribute the residual profit to young and old entrepreneurs. A failed P firm does not make any payment. Because old entrepreneurs' investment is diversified across P firms, each old entrepreneur gets

$$\mu(1 - \phi)(k_P^\alpha (\chi An_P)^{1-\alpha} - R_P l_P - wn_P),$$

where $k_P = l_P + s_P$ is the total capital, and $s_P$ is investment from old entrepreneurs.

If a P firm is successful, the young entrepreneur running it gets paid

$$\phi[k_P^\alpha (\chi An_P)^{1-\alpha} - R_P l_P - wn_P].$$

Thus young and old entrepreneurs would take the same decision regarding borrowing and labor employment, fixing private capital $s_P$.

Given capital $k_P$, P firm’s maximized gross profit (when successful) is:

$$\pi(k_P) = \max_{n_P} k_P^\alpha (\chi An_P)^{1-\alpha} - wn_P$$

The employment and entrepreneurs’ maximized gross profit (when successful) are

$$n_P = \chi^{\frac{1-\alpha}{\alpha}} \left( \frac{R_S}{\alpha} \right)^{\frac{1-\alpha}{\alpha}} k_P / \mu$$

$$\pi(k_P) = \chi^{\frac{1-\alpha}{\alpha}} R_S k_P := \rho k_P$$

The old entrepreneurs each gets $\frac{\mu(1-\phi)(k_P l_P R_P)}{\mu} = (1 - \phi)[\mu k_P - l_P R_P]$, $^{27}$

The entrepreneur’s lifetime utility maximization problem, conditional on initial success

$^{27}$Notice we divide by $\mu$ because only $\mu$ measure of old entrepreneurs has capital to invest, so each invests $k_P / \mu$, this has to be bigger than $R_S k_P / \mu$ (assumed earlier).
and subject to limited pledgeability is:

\[
\max_{c_1,c_2} \frac{c_1^{1-\frac{1}{\theta}} - 1}{1 - \frac{1}{\theta}} + \beta \frac{c_2^{1-\frac{1}{\theta}} - 1}{1 - \frac{1}{\theta}}
\]

such that

\[
c_1 = m_1 - \frac{s_{P,2}}{\mu_1}
\]

\[
c_2 = \mu_2 \frac{(1 - \phi)(\rho_2(l_{P,2} + s_{P,2}) - R_{P,2}l_{P,2})}{\mu_1}
\]

\[
R_{P,2}l_{P,2} \leq \eta \rho_2 (s_{P,2} + l_{P,2})
\]

where \(m_1\) is his or her total payoff in the first period. When \(\frac{1}{\eta} > \delta \chi^{\frac{1-\alpha}{\alpha}} > 1\), we have \(\eta \rho < R_P < \rho\), the first inequality ensures the pledgeability constraint could be binding, second inequality implies borrowing more is always profitable to the young entrepreneur, and thus the constraint actually binds. However, since \(\mu\) goes down in a recession, so does \(\delta\). The pledgeability constraint becomes non-binding if \(\delta \chi^{\frac{1-\alpha}{\alpha}} < 1\), and \(P\) firms stop borrowing. In either case, there is a unique optimizer \(s_{P,2}\), and the equilibrium is determined by the market clearing conditions:

\[
\begin{align*}
Q_t & = l_{S,t} + l_{P,t} = k_{P,t} + k_{S,t} - s_{P,t} \\
N_t & = n_{P,t} + n_{S,t} = \chi^{\frac{1-\alpha}{\alpha}} k_{P,t} + k_{S,t} \left( \frac{R_{S,t}}{A_t} \right)^{\frac{1}{1-\alpha}}
\end{align*}
\]

which admit closed-form solutions.

### 3.3 Discussion and Implications

#### Reallocation of Capital and Labor

We first examine the dynamics of factor reallocation. Similar to the Lemma 2 in Song et al. (2011), because \(k_{P,t}/k_{P,t-1} = n_{P,t}/n_{P,t-1}\), the growth rate of \(P\) firms in capital and labor share is given by

\[
1 + \gamma_t = \phi \tilde{\lambda}_t \left( 1 + \beta^{-\theta} \left( (1 - \phi) \lambda_t \right)^{1-\theta} \right)^{-1} \frac{R_{P,t} - 1}{\mu_t} 
\]

where \(\lambda_t = (1 - \eta) \rho_t R_{P,t} - \eta \rho_t \mu_t = \frac{(1-\eta)\chi^{\alpha/\mu} R_{P,t} - \eta}{\chi^{\alpha/\mu}}\) if the pledgeability constraint is binding in period \(t\), and \(\lambda_t = \rho_t \mu_t\) if it is not binding; \(\tilde{\lambda}_t = \lambda_t\) if the pledgeability is binding or non-binding for both \(t-1\) and \(t\), and \(\tilde{\lambda}_t = \lambda_t / (1 - \eta)\) if it is binding for \(t-1\) and non-binding for \(t\), and \(\tilde{\lambda}_t = \lambda_t (1 - \eta)\) if it is non-binding for \(t-1\) and binding for \(t\).
We note that the growth rate depends on private capital \( s_P \) as a state variable and on the financial frictions. More private capital and less financial friction would make private firms grow faster. For constant credit supply and workers’ population across two periods, \( 1 + \gamma_t \) completely captures the reallocation dynamics and is our main object of focus.

**Dynamics of Misallocation**

If the total output of the economy is simply the sum of individual firm outputs, we can write it as

\[
Y_t = \int y_{S,t} dS + \int y_{P,t} dP
\]

\[
TFP_t(Q_t + s_{P,t})^\alpha N_t^{1-\alpha} = k_{S,t}^\alpha (A_t n_{S,t})^{1-\alpha} + (Q_t + s_{P,t} - k_{S,t})^\alpha [\chi A_t (N_t - n_{S,t})]^{1-\alpha}
\]

\[
TFP_t \propto \lambda_{k,t}^{\alpha} \lambda_{n,t}^{1-\alpha} + \chi^{1-\alpha} (1 - \lambda_{k,t})^\alpha (1 - \lambda_{n,t})^{1-\alpha},
\]

where \( \lambda_{k,t} \) and \( \lambda_{n,t} \) are the shares of capital and labor of the S firms.

In our stylized model, \( \chi > 1 \) implies the efficient benchmark is to allocate all resources to the more productive P firms. Therefore a simple measure of misallocation of capital and labor are \( \lambda_{k,t}^{\alpha} \) and \( \lambda_{n,t}^{\alpha} \) respectively, and the distortion on aggregate TFP can be summarized by

\[
d_t = \frac{\lambda_{k,t}^{\alpha} \lambda_{n,t}^{1-\alpha}}{(1 - \lambda_{k,t})^\alpha (1 - \lambda_{n,t})^{1-\alpha}},
\]

which ranges from 0 (efficient allocation) to \( \infty \) (least efficient allocation).

**Stimulus and Recession**

We now discuss how the stimulus and recession affect the transition dynamics. At time \( t \), \( \rho_{P,t-1} \) is already determined. Decompose (4) into \( \phi(1 + \beta^{-\theta}((1 - \phi)\lambda_t)^{1-\theta})^{-1} \rho_{P,t-1} \) which is increasing in \( \phi \) (because \( \theta > 1 \)), and \( \frac{\Delta}{\rho_t} \) which is increasing in \( \mu \), and \( \eta \), decreasing in \( b \), and independent on \( Q \).

First, we note that \( \frac{\partial(1 + \gamma_t)}{\partial Q} < 0 \). Intuitively, an increase in Q will cause \( R_{S,t} \) to fall, then \( \lambda_t \) (which reflects private investment) decreases while \( \frac{\Delta}{\rho_t} \) (which is related to the financial frictions) does not change, therefore \( \gamma_t \) decreases. This means that regardless of the economic condition and whether the pledgeability constraint is binding, a credit expansion disproportionally supports S firms and slows down the reallocation of resources to P firms. Economically, as \( R_S \) goes down, S firms demand more capital and labor, driving up the wage. Consequently, the P firms’ capital productivity is lower. Foreseeing this, for a given payoff when they are young, entrepreneurs consume more and invest less in the private fund because the marginal benefit of private investment (P firms’ capital productivity) is lower. This slows down the growth of private capital in the production, which reduces \( k_P \) no matter the pledgeability constraint binds or not. Therefore, a credit...
expansion slows down the growth of P firms in terms of shares of the economy, or even reverse the reallocation of labor and credit from S firms to P firms. Similarly, we note \( \frac{\partial (1+\gamma_t)}{\partial \mu} > 0 \) because \( \lambda \) and \( \tilde{\lambda} \) are both increasing in \( \mu \). An economic downturn also slows down the reallocation process by limiting the saving of young entrepreneurs.

From this, we conclude that credit expansion or decline in economic environment in the presence of credit allocation friction both slow down P firms’ growth.\(^\text{28}\) Moreover, the cross partial \( \frac{\partial^2 (1+\gamma_t)}{\partial \mu \partial Q} \) can be negative for a wide range of parameters, which implies that credit expansion in bad economic environment may reduce efficient factor reallocation even more and increase the likelihood of reversal (interaction effect). We illustrate these predictions of the model in terms of credit and labor share of S firms in Figure 2. The upper panel shows the case in which the economy experiences a permanent change in credit supply (higher \( Q \)) and deterioration of economic environment (lower \( \mu \)). The lower panel shows the case in which the economy experiences a temporary change (6 periods) in both credit supply and economic environment, after which the economic conditions and credit supply go back to their original levels. Notice how, in the latter case, it still takes an additional 6 periods for the economy to get back to the original reallocation path. This delay in the reallocation of resources from S firms to P firms can have significant impact on real outputs and economic growth.

**Financial Frictions**

Next we examine how reducing financial frictions affects transition dynamics. Because \( \frac{\partial (1+\gamma_t)}{\partial b} < 0 \), reducing the interest rate friction always facilitates the reallocation of resources from S firms to P firms. One might think that increasing \( \eta \) or reducing \( b \) (same as increasing \( \delta \) and fixing \( \mu \)) drives up \( R_S \) when pledgeability constraint is binding. All these in turn leads to higher \( \lambda \). This is in general not true due to a general equilibrium effect. Reducing the financial frictions make P firms demand more loan and labor, but the latter could be more dominant, resulting in increased wage and a larger decrease in loan demand from S firms. Subsequently interest rate could decrease and entrepreneurs borrow more and save less private capital, slowing down the reallocation. That said, if P firms are sufficiently productive, \( \frac{\partial (1+\gamma_t)}{\partial \delta} > 0 \), i.e., reducing the pledgeability constraint also speeds up the reallocation. One sufficient condition is

\[
\chi > \left[ \frac{1 - \delta + \alpha \delta - \alpha \delta \eta}{\alpha \delta + \delta \eta - \alpha \delta \eta - \delta^2 \eta} \right]^{\frac{1}{1-\alpha}}
\]

\(^{28}\)This slow-down of the reallocation process can also be obtained in the original model in Song et al. (2011) is we exogenously lower interest rates. However, we need the additional assumption that the pledgeability constraint is always binding and it is hard to explain why S and P firms coexist in the long-run. Our model describes China’s situation better in that China is not a small open economy with exogenous interest rate and empirically we do observe bailouts of SOEs and differential interest rates. The interest rate friction also interacts with the pledgeability friction to make the reallocation process more likely reversed.
which still satisfies $\eta \delta \chi^{-\alpha} < 1$ (pledgeability constraint binding).

Interest rates are exogenous in Song et al. (2011), and the interest rate friction is absent. Therefore if a private firm is sufficiently productive to attract private capital, it is always the case that entrepreneurs would borrow up to the pledgeability constraint. This implies that relaxing the pledgeability constraint always facilitates the reallocation of resources from less productive firms to more productive firms. Equation (4), however, is increasing in $\lambda$, which can be increasing in $\eta$ if and only if $\delta \chi^{-\alpha} > 1$. Hence we see that in addition to directly contributing to the misallocation of credits, $\delta$ plays an important role in that it relaxes the pledgeability constraint and once $\delta < \chi^{-\alpha}$, increasing $\eta$ would not mitigate misallocation of resources because it is no longer binding. Therefore, modeling both the interest rate friction and the pledgeability friction not only makes the model more realistic, but also illustrate how various channels could be at work under different economic environments. Correspondingly, policies for mitigating credit misallocation could drastically differ.

### Steady States and Permanent Impact

To derive the steady states of the economy, rewrite the steady states (SS) eq(4),

$$\phi \lambda (1 + \beta^{-\theta}((1 - \phi)\lambda)^{1-\theta})^{-1} - 1 = 0$$  \hspace{1cm} (7)

Denote the unique positive solution by $\lambda_0$.

Inverting the definition of $\lambda$, we can solve for the steady states interest rates. We can then solve for the steady-state level of capital and labor shares of P firms from eq(2)-(3), which are proportional to the only state variable in the economy $s_P$. Depending on the credit supply, economic environment, and financial frictions, the steady state of the economy can be one of the three types we describe next. In particular, endogenizing interest rates allows us to analyze the eventual level of factor re-allocation, which does not obtain in the partial equilibrium in Song et al. (2011).

First, P firms could replace S firms eventually. This case happens when $Q$ is small relative to $s_P$ because P firms are more reliant on private capital and are less disadvantaged in bank credit allocation. This could also happen when $\mu$ is large enough that private capital $s_P$ can grow very quickly. Second, S firms could completely crowd out P firms in the long run. This happens when $Q$ is large relative to $s_P$ or $\mu$ is small. In this case,

$$R_S = \alpha \left(\frac{A}{Q}\right)^{1-\alpha}, \quad k_S = Q, \quad k_P = 0.$$

The most interesting case occurs when S and P firms co-exist. Whether the pledgeability constraint is binding or not, steady-state $s$ is decreasing in $Q$ and increasing in $\mu$. Therefore, when $Q$ increases or $\mu$ decreases, $s_P$ falls, so does $l_P$ (loans borrowed) and
Economic recession and credit expansion have long-term impacts. Cross partial in $Q$ and $\mu$ is zero, therefore whether credit expansion is cyclical or counter-cyclical does not matter for steady state market share of P firms.

To further analyze the effect of $b$ and $\eta$ on the level when the pledgeability constraint is binding, we can show that $\frac{\partial s}{\partial \eta}$ is positive if and only if inequality (6) holds, and $\frac{\partial s}{\partial b} < 0$ always holds. Therefore, reducing interest rate friction always increases the fraction of more productive firms in the steady state, and reducing limited pledgeability constraint increases the fraction if P firms are sufficiently more productive relative to S firms. When $\delta^\alpha \chi^{1-\alpha} < 1$, the pledgeability constraint is not binding, and increasing pledgeability does not affect the steady state level of $s$.

4 Data Description

The main data sources are the Annual Survey of Industrial Firms of the China’s National Bureau of Statistics and the bank branch location database of the China Banking Regulatory Commission.

The Annual Survey of Industrial Firms covers firms operating in the manufacturing, mining, and utility sectors from year 1998 to 2013. All firms with annual sales above a given monetary threshold are surveyed, making the survey effectively a Census of medium to large size non-publicly-traded Chinese firms. Until 2010, this threshold was set at 5 million CNY (730,000 USD), and then raised to 20 million CNY (3 million USD) from 2011 onward.\textsuperscript{29} Table 1 reports main summary statistics by year for the firms covered in the Annual Industrial Survey.

The firm-level variables of interest are long term liabilities, total assets, total fixed assets, total sales and number of employees. We use annual changes in long-term liabilities as a proxy for new bank credit, and annual changes in total fixed assets as a proxy for investment. Another key variable in our analysis is state ownership. The Annual Survey of Industrial Firms reports the legal registration status of each firm. One possible definition of SOE is, therefore, firms that are legally registered as “state-owned”. However, as underlined by Hsieh and Song (2015), this definition does not take into account that firms that are ultimately controlled by a state-owned company can actually be legally registered as foreign firms, or limited liability firms. Therefore, following Hsieh and Song (2015), we define a firm as SOE if either the share of registered capital owned by the state is equal or larger than 50 percent or if the state is reported as the controlling shareholder. Columns (6) and (7) of Table 1 report, by year, the share of firms in our sample with these characteristics. In column (8) we report the share of firms that respond to the Hsieh and Song (2015) definition of SOE. As shown, all these measures of state control have

\textsuperscript{29}Until 2006, all firms registered as state-owned were surveyed. After 2006, the same threshold is applied to both private firms and firms registered as state-owned.
been decreasing over time. For example, the government was the controlling shareholder of 32% of firms in our sample in 1998, and only of 6% of firms a decade later, in 2008. Interestingly, the share of state-controlled firms have stabilized since then.

We also use data on bank branch location from the China Banking Regulatory Commission to construct bank specific proxies for the share of their aggregate corporate lending allocated to different cities. As explained in section 5, the key variable for our analysis is the number of branches of each bank in each city in the year 2005, our baseline year for the empirical analysis. We define cities as the 2nd administrative division of the Chinese territory, right below provinces. There are 389 cities in our dataset, 332 of which have at least one bank branch in operation in 2005. Figure 5 shows the geographical distribution of bank branches of all banks in our dataset in 2005.

5 Identification Strategy

5.1 Bartik-style Credit Supply Shock

In this section we study empirically the allocation of bank credit across manufacturing firms and its real effects during the economic stimulus years in China. The main identification challenge we face is to isolate changes in firm borrowing that are solely driven by credit supply shocks from changes driven by demand or investment opportunities.

In what follows we propose a measure of firm exposure to the credit supply shock generated by the stimulus plan. Empirically, we observe that different banks have expanded their lending more than others during the stimulus years. These differences can be driven by their differential exposure to the stimulus specific policies such as changes in lending quotas and lower reserve requirements. In addition, these differences can be driven by changes in credit demand from their borrowers. In the spirit of Bartik (1991), we exploit variation in bank lending at national level during the stimulus years to construct a firm-specific measure of exposure to the credit increase generated by the stimulus plan.\footnote{See Bartik (1991). The Bartik identification strategy has been largely used in the labor literature starting from Blanchard, Katz, Hall, and Eichengreen (1992). See Greenstone, Mas, and Nguyen (2015) for an application to credit markets.}

Ideally, the credit shock to which firm $i$ is exposed would be equal to:

$$\tilde{l}_{it} = \sum_b \omega_{bi,t=0} \times \Delta Loan_{b-i,t}$$

where $b$ indexes banks, $i$ indexes firms and $t$ indexes time. The weights $\omega_{bi,t=0}$ capture the strength of the relationship between firm $i$ and bank $b$ in the pre-stimulus period. The variable $\Delta Loan_{b-i,t}$ captures new lending of bank $b$ at national level, excluding lending going to firm $i$. In words, equation (8) uses variation in national lending by banks with
which firm \(i\) has a pre-existing relationship to construct an instrument for firm \(i\) lending that is plausibly exogenous with respect to firm \(i\) specific demand.

One important caveat in our setting is that we observe borrowing at firm-level and total corporate lending at bank level, but we do not observe specific bank-firm relationships. Therefore, we write a modified version of equation (8) as follows:

\[
\widetilde{l}_{ct} = \sum_b \omega_{bc,t=0} \times \Delta Loans_{bt} \tag{9}
\]

where \(\omega_{bc,t=0}\) is the lending market share of bank \(b\) in city \(c\), as captured by the share of bank \(b\) branches operating in city \(c\) as a share of total bank branches in city \(c\). We construct \(\omega_{bc,t=0}\) using detailed data on branch addresses from the China Banking Regulatory Commission. Figure 6 shows the geographical distribution of the branch network of four Chinese banks – two large national banks and two small regional banks – as an illustrative example. We define this measure in 2005, in the pre-stimulus period, to avoid endogenous branch openings polluting our estimates. This allows us to link firm-level borrowing to bank-level lending exploiting variation in the geographical location of the branch network of Chinese banks. In other words, \(\omega_{bc,t=0}\) captures the strength of the link between bank \(b\) and firm \(i\) in the pre-stimulus years.

Similarly to other papers that exploit pre-existing banking relationships to study the effect of changes in credit supply at bank level on firm level outcomes, this identification strategy relies on two assumptions.\(^{31}\) First, borrower-lender relationships have to be persistent over time such that firms can not easily switch from one lender to another. In our setting, if firms can easily reshape their portfolio of lenders, then variation in \(\widetilde{l}_{ct}\) should not explain variation in actual firm lending.

The second assumption is that cross-sectional variation in bank lending during the stimulus years is uncorrelated with a bank’s borrowers (firms) changes in credit demand. To illustrate the nature of this assumption, we write down a simple model of credit demand and supply. Define \(Loans_{bt}\) as the national level of corporate lending of bank \(b\) at time \(t\). As in Greenstone et al. (2015), let us rewrite the national lending of a given bank as a function of supply and demand shifters:

\[
\Delta Loans_{bt} = D_t^c Q_{bt}^\lambda
\]

\[
= (\Pi_p (\Pi_c D_{ct}^{pc})^{\mu_p} \Pi_j D_{jt}^{\nu_j}) \omega Q_{bt}^\lambda
\]

where \(D_t\) is a national-level demand shifter and \(Q_{bt}\) is a bank-level supply shifter. The subscript \(p\) identifies provinces, which are a collection of cities indexed by \(c\), while \(j\) indexes sectors. The national level demand shifter is therefore a collection of local demand shifters and sector specific demand shifters. The supply shifter, instead, depends on bank-

\(^{31}\)See, for example, Greenstone et al. (2015) and Chodorow-Reich (2014).
specific characteristics such as the bank’s overall financial health or its cost of funds. The simplifying assumption is that all banks face the same national demand for credit no matter their geographical specialization.\textsuperscript{32}

It is useful to plug this simple definition of bank lending at national level into equation (9) to obtain:

\[
\tilde{l}_{ct} = \sum_{b} \omega_{bc,t=0}(\Pi_{p}(\Pi_{c}D_{ct}^{\mu_p})^{\mu_p}\Pi_{j}D_{jt}^{\nu_j})^{\nu_j}Q_{bt}^{\lambda}
\] (10)

Equation (10) shows that local shocks to demand in city \( c \) and province \( p \) where firm \( i \) operates enter into the definition of \( \tilde{l}_{ct} \), violating the identification assumption. Similarly, national shocks to demand in sector \( j \) where firm \( i \) operates also enter into the definition of \( \tilde{l}_{ct} \). One potential solution often used in the construction of Bartik shocks is to remove lending to the specific location or sector where firm \( i \) operates from the summation in equation (10). In our setting, we cannot pursue this route. This is because we do not directly observe lending of bank \( b \) to a specific location or sector. In what follows, we propose a simple methodology to back out Bartik-style credit supply shocks in frameworks where firm-level outcomes and bank-level lending data are available but bank-firm relationships are not directly observable.

Our solution to this identification challenge relies on using province and sector fixed effects interacted with year dummies. To illustrate this strategy, let us rewrite equation (10) as follows:

\[
\tilde{l}_{ct} = (\Pi_{p}(\Pi_{c}D_{ct}^{\mu_p})^{\mu_p}\Pi_{j}D_{jt}^{\nu_j})^{\nu_j} \sum_{b} \omega_{bc,t=0}Q_{bt}^{\lambda}
\]

Taking logs on both sides we obtain:

\[
\log \tilde{l}_{ct} = \omega \mu_p \log(\Pi_{p}(\Pi_{c}D_{ct}^{\mu_p})) + \omega \nu_j \log(\Pi_{j}D_{jt}) + \log \sum_{b} \omega_{bc,t=0}Q_{bt}^{\lambda}
\] (11)

Notice that the first element of this equation is the exposure to local demand shifters, the second element is the exposure to sector-specific demand shifters, and the third element captures the average credit supply shifter across banks operating in the city where firm \( i \) operates. Our objective is to single out the effect of this last element on firm borrowing.

To this end, let us write down a simple equation that relates actual borrowing of firm \( i \) to its exposure to national level changes in bank lending. We add to this specification the interaction of province and year fixed effects, and the interaction of sector and year

\textsuperscript{32}One way to think about this assumption is that firms post credit applications to all banks every period no matter their location or sector of operation.
fixed effects, as follows:

\[ \log l_{icjt} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \log \tilde{l}_{ct} + \varepsilon_{icjt} \] (12)

Equation (12) is the equation that we estimate in the data. To show that the coefficient \( \beta \) on \( \log \tilde{l}_{ct} \) captures exclusively changes in credit supply, let us substitute in equation (12) the definition of \( \log \tilde{l}_{ct} \) obtained in equation (11):

\[ \log l_{icjt} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \omega_p \log(\Pi_p(\Pi_c D_{ct}^{pc})) + \beta \omega j \log(\Pi_j D_{jt}) + \beta \log \sum_b \omega_{bc,t=0}Q_{bt}^\lambda + \varepsilon_{icjt} \] (13)

Notice from equation (13) that fixed effects at sector level interacted with time dummies (\( \alpha_{jt} \)) fully capture sector-specific demand shocks. However, fixed effects at province level interacted with time dummies still do not fully capture city-level demand shocks. Therefore, our identification relies on the assumption that credit demand shifters are highly correlated across cities within the same province. This is a strong assumption that we will try to partially relax in the empirical analysis by controlling for initial city characteristics interacted with year fixed effects. These controls will capture city-level demand shifters to the extent that differences in business cycle across cities within the same province are correlated with differences in initial city characteristics, such as income per capita, size, or share of rural population.

Under this assumption, equation (13) can be rewritten as:

\[ \log l_{icjt} = \delta_t + \delta_{pt} + \delta_{jt} + \beta \log \sum_b \omega_{bc,t=0}Q_{bt}^\lambda + \varepsilon_{icjt} \] (14)

where: \( \delta_t = \alpha_t; \delta_{pt} = \alpha_{pt} + \beta \omega p \log(\Pi_p(\Pi_c D_{ct}^{pc})); \delta_{jt} = \alpha_{jt} + \beta \omega j \log(\Pi_j D_{jt}) \)

Similarly to a Bartik-style shock in which the econometrician observes and can therefore remove from national variation in lending the loans to a specific county, we are effectively purging our estimate from time varying common shocks in both the province and the sector in which firm \( i \) operates. Therefore, the coefficient \( \beta \) should capture variation in firm-level borrowing that is exclusively driven by bank level credit supply shocks. In other words, when estimating equation (12) we are effectively comparing firms that are subject to the same province-level demand shocks and to the same sector-level demand shocks but are differently exposed to bank national credit supply shocks.
6 Empirical results

In this section we report the main empirical results. In section 2.1, we documented a set of basic stylized facts that are present in our data. In particular, we showed how manufacturing firms covered by the Annual Industrial Survey experienced a sharp increase in long term debt during the two years of the stimulus plan (2009 and 2010). We also documented how this increase in long term debt has been larger for state owned firms relative to private firms, and for firms with lower marginal productivity of capital. The timing of the differential increase in long term debt for different firms is suggestive of this effect being driven by the stimulus plan. However, we cannot rule out other explanations such as different exposure of certain sectors to the contemporaneous decrease in demand due to the global financial crisis. Therefore, in this section we use the identification strategy proposed in section 5.1 to plausibly identify exposure to credit supply shocks and establish our results on credit allocation.

6.1 Bartik-style Bank Credit Supply Shock

In section 5.1 we propose an identification strategy that allows us to plausibly identify exposure to credit supply shocks at the firm level. Armed with this measure, in this section we study the allocation of credit across firms during the years of the stimulus plan in China, as well as its real effects in terms of investment and firm growth. To this end we proceed in three steps. In the first step, we show that our measure of exposure to bank credit supply shocks effectively explains variation in firm borrowing. In a second step, we study the allocation of credit across firms by interacting our measure of exposure to credit supply shocks with initial firm characteristics. In this second step we are particularly interested in investigating whether banks allocated funds differently during the stimulus years between state owned firms and non state owned firms, or between firms with different initial levels of marginal product of capital. Finally, in a third step, we investigate the real effects of credit allocation during the stimulus years.

6.1.1 Bank Credit Supply Shock and Firm Borrowing

We start by testing the effect of bank level credit supply shocks on firm borrowing. The baseline equation that we estimate is equation (12) described in section 5.1, which we report here for the reader’s convenience:

\[
\Delta y_{icjt} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \log \tilde{l}_{ct} + \varepsilon_{icjt}
\]  

where \(\Delta y_{icjt}\) is an outcome that varies across firms indexed by \(i\). The subscript \(c\) identifies cities, \(p\) identifies provinces, \(j\) identifies 4-digit sectors and \(t\) identifies years. The
coefficient of interest is $\beta$, that capture the effect of bank credit supply shock in a given city and year on changes in firm-level outcomes. Our measure of bank credit supply shock is defined as follows:

$$\tilde{l}_{ct} = \sum_b \omega_{bc,t=0} \times \Delta \text{Loans}_{bt},$$

(16)

where $\omega_{bc,t=0}$ is our proxy for bank $b$ lending market share in city $c$, and it is constructed as the share of branches of bank $b$ in city $c$ over total bank branches operating in city $c$ in year 2005. The variable $\Delta \text{Loans}_{bt}$ is the yearly change in the stock of outstanding corporate loans of bank $b$ between year $t - 1$ and $t$. The specification includes province and sector fixed effects interacted with time fixed effects, to capture local demand shock as well as industry specific demand shocks, as showed in equation (14).

As discussed in section 5.1, our identification strategy relies on credit demand shocks being similar across cities in a given province. However, as shown in Table 3, exposure to credit supply shock during the stimulus years is in fact correlated with some initial city characteristics. For example, cities with larger exposure to credit supply shock used to have around 10% higher GDP per capita in the pre-stimulus period (all city characteristics are observed in 2005). Therefore, if cities with different initial level of development – as captured by GDP per capita – within a given province experienced different credit demand during this period, our estimates might be capturing these trends rather than credit supply shocks. To partially address this concern, we add to the equation to be estimated city-level initial characteristics interacted with year fixed effects. In particular, we control for those initial characteristics that are correlated with exposure to credit supply shock during stimulus years: GDP per capita, population and population density. Another concern is that firms that are exporters might have received a negative demand shock during the stimulus years, due to lower global demand. Therefore, we also add export status, in addition to size and age as firm-level controls. The final equation to be estimated is reported below:

$$\Delta y_{ict} = \alpha_t + \alpha_p + \alpha_jt + \beta \log \tilde{l}_{ct} + \gamma X_{i,t-1} + Z_{c,t=0} \times \alpha_t + \epsilon_{ict}$$

(17)

where $X_{i,t-1}$ are firm-level controls and $Z_{c,t=0}$ are city characteristics observed in 2005. Table 4 reports the results of estimating equation (17) when the outcome variable is the change in long-term liabilities between year $t - 1$ and year $t$, divided by revenues in year $t - 1$.\(^{33}\) To insure comparability over time we restrict our sample to firms with annual sales above 20 million CNY, for which we effectively observe the whole population in every year. Notice that our data on bank-level corporate loans ($\Delta \text{Loans}_{bt}$) is only available starting

\(^{33}\)All monetary variables are CPI adjusted.
from 2008, which implies we estimate equation (15) for the time period 2009 to 2013.

The estimated coefficients reported in Table 4 show that firms with larger exposure to bank credit supply shocks experience a larger increase in borrowing. In column 1 we estimate equation (15) including year fixed effects, as well as province and sector fixed effects interacted with year fixed effects. In column 2 we include the set of initial city characteristics interacted with year fixed effects. Finally, in column 3 we estimate the full specification showed in equation 17, including firm-level controls. As shown, the size of the estimated coefficient on the bank credit supply shock is relatively stable across specifications, and precisely estimated in all specifications. The magnitude of the estimated coefficient reported in column 3, our preferred specification, indicates that a firm with a 1 standard deviation larger exposure to bank credit supply shocks experiences a .19 percentage point larger increase in long-term liabilities as a share of revenues.

6.1.2 Credit Allocation under Stimulus Plan

In the previous section we showed how our measure of firm exposure to bank credit supply shocks predicts actual borrowing at firm level across all years between 2009 and 2013. Our objective, in this section, is to study the allocation of new loans by banks during the stimulus years 2009 and 2010. In particular, we are interested in studying whether banks allocated funds differently during the stimulus years between state owned firms and non state owned firms, as well as between firms with different initial levels of marginal product of capital. To this end, we estimate the following version of equation (15):

\[
\Delta y_{ict} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta_1 \log \tilde{l}_{ct} \times C_{icjt-1} + \beta_2 \log \tilde{l}_{ct} + \beta_3 C_{icjt-1} + \gamma X_{i,t-1} + Z_{c,t} \times \alpha_t + \varepsilon_{icjt},
\]

where the variable \( C_{icjt-1} \) is a pre-determined firm characteristic and captures, depending on the specification, either the ownership status of firm \( i \) or its initial marginal product of capital. The coefficient of interest is \( \beta_1 \), which captures the differential effect of exposure to bank credit supply shocks on firm borrowing depending on initial firm characteristics. We focus on two main firm characteristics: state-ownership and initial marginal productivity of capital, both defined in year 2007.\(^{34}\)

Table 5 reports the results of estimating equation (18) when the outcome variable is the change in long-term liabilities between year \( t - 1 \) and year \( t \), divided by revenues in year \( t - 1 \). We start by testing the main effect of \( \tilde{l}_{ct} \) on firm borrowing. Columns 1 and 2 report the results of estimating the effect of exposure to bank credit supply shock

\(^{34}\)As discussed in the section 4 and showed in Table 1, the variable \( I(\text{State Owned Firm}) \) is not available in the years 2008 and 2009.
on firm borrowing. This is to check that our measure of exposure explains changes in firm long-term liabilities also when we focus on the stimulus years 2009 and 2010. The estimated coefficient on $\tilde{\lambda}_t$ is positive, precisely estimated, and robust to controlling for firm characteristics and differential trends for cities with different initial characteristics.

In columns 3 and 4, we report the results of estimating equation (18) when $C_{icjt-1}$ captures state-ownership of firm $i$. The estimated coefficient $\beta_1$ is positive and significant in both specifications. This indicates that state-owned firms experienced a relatively larger increase in borrowing with respect to private firms when exposed to the same bank credit supply shock. The estimated coefficient $\beta_2$ is also positive (although not statistically significant when adding all controls), which indicates that the differential effect in firm borrowing between SOE and private firms is on top of a positive increase in private firms borrowing in response to a credit supply shock. However, notice how the magnitude of the estimated $\beta_2$ is smaller in size with respect to columns 1 and 2. Taken together, the magnitudes of the estimated $\beta_1$ and $\beta_2$ coefficients in column 4 indicates that, in response to a 1 standard deviation change in exposure to credit supply shock, state-owned firms experience a .31 percentage points increase in new loans, versus the 0.03 percentage points for private firms (both as a share of firm revenues). In other words, the elasticity of firm borrowing to the exposure to credit supply shock is around 10 times larger for state-owned firms than for private firms during the stimulus years. Finally, notice that the estimated coefficient on the main effect of state-ownership status is negative and significant. Our interpretation of this coefficient is that, in the absence of a credit supply shock generated by the stimulus plan, state-owned firms would experience a lower increase in borrowing with respect to private firms.

Finally, in column 5 and 6 of Table 5, we report the results of estimating equation (18) when $C_{icjt-1}$ is equal to the firm-level marginal product of capital in year 2007. Marginal product of capital is defined as the logarithm of industrial value added divided by book value of fixed assets. The estimated coefficient on the interaction between exposure to credit supply shock and initial marginal product of capital is negative and precisely estimated. This indicates that, when exposed to the same bank credit supply shock, firms with lower initial marginal product of capital experienced a relatively larger increase in borrowing with respect to firms with initially higher marginal product of capital. The magnitude of the estimated coefficient $\beta_2$ indicates that firms with a 1 standard deviation larger $MPK$ experienced a 0.42 percentage points lower increase in new loans (as a share of revenues) during the 2009-2010 period. This result suggests an increase in credit misallocation during stimulus years. In addition, it is consistent with state-owned firms experiencing a relatively larger increase in new loans during the stimulus years with

\footnote{In this definition marginal product of capital is equivalent to average product of capital. The underlying assumptions are identical labor share and mark-ups within a given sector.}
respect to private firms. Notice that both main effects on the exposure to the credit supply shock and on the initial marginal product of capital are positive and significant. In particular, the positive estimated coefficient on log $MPK$ indicates that, net of the credit supply shock, firms with higher marginal product of capital would have experienced a higher increase in new loans during the stimulus years.

### 6.1.3 Real Effects of Credit Allocation

In the previous section we showed that, during the stimulus years, bank credit supply has disproportionately favored state-owned firms and firms with lower initial marginal product of capital. In this section we investigate the real effects of this credit allocation. In particular, we focus on firm investment. To this end, we estimate equation (18) using as outcome variable the change in total fixed assets between year $t - 1$ and year $t$, again scaled by total revenues in year $t - 1$.

Results are reported in Table 6. As in Table 5, we start by separately testing the main effect of firm exposure to credit supply shock ($\tilde{l}_{ct}$) on firm investment. The estimated coefficients on $\tilde{l}_{ct}$ reported in columns 1 and 2 are positive and precisely estimated. The magnitude indicates that a firm with a 1 standard deviation larger exposure to bank credit supply shock experience a 0.3 percentage points larger increase in total fixed assets as a share of revenues.

In columns 3 and 4 we report the results of estimating equation (18) when the variable $C_{icjt-1}$ captures state-ownership. The estimated coefficient $\beta_1$ on the interaction between exposure to credit supply shock and state-ownership is positive but not statistically different from zero at standard levels of significance. This suggests that, despite the difference in firm borrowing, state-owned firms and private firms with same exposure to the credit supply shock experience similar increase in investment. In columns 5 and 6 we report the results of estimating equation (18) when the variable $C_{icjt-1}$ is the initial marginal product of capital. In this specification we find a negative and statistically significant coefficient on the interaction, and the estimated $\beta_1$ is stable in size when adding controls. This suggests that firms with lower initial marginal product of capital invested relatively more during the stimulus years. In particular, the magnitude of the estimated coefficient $\beta_1$ indicates that firms with a 1 standard deviation larger $MPK$ experienced a 0.96 percentage points lower increase in investment (as a share of revenues) during the 2009-2010 period. We interpret this finding as evidence of misallocation of physical capital. Notice that, as in Table 5, the estimated coefficient on the main effect of marginal product of capital is positive and significant. This indicates that, in absence of exposure to credit supply shock, initially more productive firms would experience a higher increase in capital investment.

\[36\text{In our data, state-owned firms display, on average, lower marginal product of capital with respect to private firms. This finding has already been pointed out by Hsieh and Song (2015).}\]
7 Conclusions

This paper shows that large scale government-led stimulus programs during economic downturns in countries with severe financial frictions can generate an increase in capital misallocation. That is, new credit is allocated disproportionately more to firms with lower initial marginal productivity of capital but higher connection to the government.

Using plausibly exogenous changes in bank credit supply, we study credit allocation across different types of firms during the 4-Trillion CNY stimulus plan in China. Our results show that, during the stimulus years of 2009 and 2010, bank credit was disproportionately allocated towards state-owned or state-controlled firms and firms with lower initial marginal productivity of capital. In addition, larger allocation of bank credit to these firms had real effects in terms of larger capital investment. Our results are informative for developing countries that undertook large stimulus programs in response to the Great Recession and whose credit markets are plagued by severe frictions.
References


Figures and Tables

Figure 1: Credit Flows from Financial System to Real Economy

Notes: Source: Total Social Financing, People Bank of China
Figure 2: Dynamics of Resource Allocation
Shares of Bank Credits and Labor for P Firms

Notes: Based on simulation using $\chi = 1.57$ (Song et al. (2011)), $\eta = 0.36$ (WB Doing Business), $A = 1$, $\alpha = 0.35$, $\phi = 0.5$, $\beta = 0.95$, $N = M = 1$. Panel (a) and (b) illustrate the scenario that recession and credit expansion do not revert, whereas (c) and (d) depict the scenario that the economy recovers after 6 periods, at which the government reduces the credit supply to the original level. The four lines from top to bottom represent an economy (1) without recession and credit expansion, (2) with recession but without credit expansion, (3) with credit expansion in boom, (4) with credit expansion in recession respectively. In the presence of financial frictions, deteriorating economic environment and credit expansion slow down the reallocation of resources from S firms to P firms.
Figure 3: Long Term Liabilities: Level and Change

Notes: Source: National Bureau of Statistics, Annual Industrial Survey
Figure 4: Bank Required Reserve Ratio

Notes: Source: WIND
Figure 5: Geographical distribution of bank branches

![Geographical distribution of bank branches](image1)

**Notes**: Source: CBRC

Figure 6: Geographical Location of Bank Branch Networks
Illustrative Examples

![Illustrative Examples](image2)

**Notes**: Source: CBRC
Figure 7: State-Ownership and New Loans Over Time
Estimated Coefficients and 95pc Confidence Intervals

Notes: The figure shows the estimated coefficient $\beta$ in equation (1) when $C_{icjt-1} = f(\text{State Owned Firm})_{icjt-1}$, along with 95 percent confidence intervals, when the outcome variable at firm level is change in long term liabilities between $t-1$ and $t$ over revenues at $t-1$. We estimate equation (1) separately for each sub-period reported on the $x$-axis. Each regression includes time, city and 4-digit sector fixed effects. Standard errors are clustered at the firm level. The dashed blue line captures the introduction of a new policy for SOE introduced by the Chinese government in September 1999 that favored the privatization of state-controlled firms (especially the small ones). The dashed red line instead captures the introduction of the stimulus plan in November 2008.
Figure 8: Share of SOE Firms
Chinese Industrial Sector - 1998 to 2013

Notes: Source: Annual Industrial Survey. We restrict our sample to firms with annual sales above 20 million CNY (CPI adjusted, in 2000 CNY) and with non-missing data for the following monetary variables: long-term liabilities, total assets and annual sales. We define SOE according to the definition proposed by Hsieh and Song (2015).
Table 1: Summary Statistics
Annual Survey of Industrial Firms, 1998-2013

<table>
<thead>
<tr>
<th>year</th>
<th>N firms (1)</th>
<th>Long-term liabilities (2)</th>
<th>Total Assets (3)</th>
<th>Annual Sales (4)</th>
<th>Employment (5)</th>
<th>Gov ownership share ≥ 50% (6)</th>
<th>Gov control shareholder (7)</th>
<th>State-Owned Enterprise (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>57,908</td>
<td>31,837</td>
<td>158,529</td>
<td>97,050</td>
<td>695</td>
<td>0.272</td>
<td>0.319</td>
<td>0.326</td>
</tr>
<tr>
<td>1999</td>
<td>60,415</td>
<td>31,864</td>
<td>165,416</td>
<td>103,124</td>
<td>702</td>
<td>0.244</td>
<td>0.282</td>
<td>0.298</td>
</tr>
<tr>
<td>2000</td>
<td>66,829</td>
<td>29,600</td>
<td>162,084</td>
<td>114,584</td>
<td>628</td>
<td>0.201</td>
<td>0.247</td>
<td>0.260</td>
</tr>
<tr>
<td>2001</td>
<td>72,823</td>
<td>26,824</td>
<td>157,781</td>
<td>114,487</td>
<td>553</td>
<td>0.166</td>
<td>0.212</td>
<td>0.223</td>
</tr>
<tr>
<td>2002</td>
<td>82,893</td>
<td>24,243</td>
<td>151,198</td>
<td>118,731</td>
<td>520</td>
<td>0.137</td>
<td>0.179</td>
<td>0.190</td>
</tr>
<tr>
<td>2003</td>
<td>98,769</td>
<td>22,374</td>
<td>153,260</td>
<td>134,337</td>
<td>473</td>
<td>0.107</td>
<td>0.140</td>
<td>0.151</td>
</tr>
<tr>
<td>2004</td>
<td>129,406</td>
<td>19,368</td>
<td>143,604</td>
<td>136,718</td>
<td>410</td>
<td>0.077</td>
<td>0.104</td>
<td>0.111</td>
</tr>
<tr>
<td>2005</td>
<td>148,867</td>
<td>17,818</td>
<td>139,111</td>
<td>144,236</td>
<td>385</td>
<td>0.059</td>
<td>0.083</td>
<td>0.091</td>
</tr>
<tr>
<td>2006</td>
<td>175,625</td>
<td>18,032</td>
<td>143,025</td>
<td>157,446</td>
<td>355</td>
<td>0.048</td>
<td>0.082</td>
<td>0.084</td>
</tr>
<tr>
<td>2007</td>
<td>207,987</td>
<td>16,326</td>
<td>140,687</td>
<td>162,350</td>
<td>331</td>
<td>0.039</td>
<td>0.071</td>
<td>0.073</td>
</tr>
<tr>
<td>2008</td>
<td>200,244</td>
<td>15,879</td>
<td>127,376</td>
<td>156,299</td>
<td>298</td>
<td>na</td>
<td>0.058</td>
<td>na</td>
</tr>
<tr>
<td>2009</td>
<td>248,726</td>
<td>19,270</td>
<td>148,551</td>
<td>166,809</td>
<td>296</td>
<td>na</td>
<td>0.058</td>
<td>na</td>
</tr>
<tr>
<td>2010</td>
<td>236,265</td>
<td>27,125</td>
<td>117,218</td>
<td>241,533</td>
<td>530</td>
<td>0.050</td>
<td>0.091</td>
<td>0.092</td>
</tr>
<tr>
<td>2011</td>
<td>210,025</td>
<td>28,489</td>
<td>210,667</td>
<td>243,673</td>
<td>391</td>
<td>0.037</td>
<td>0.061</td>
<td>0.082</td>
</tr>
<tr>
<td>2012</td>
<td>204,585</td>
<td>31,370</td>
<td>229,617</td>
<td>255,051</td>
<td>375</td>
<td>0.043</td>
<td>0.063</td>
<td>0.087</td>
</tr>
<tr>
<td>2013</td>
<td>225,856</td>
<td>31,093</td>
<td>229,196</td>
<td>257,863</td>
<td>473</td>
<td>0.049</td>
<td>0.061</td>
<td>0.088</td>
</tr>
</tbody>
</table>

All years 151,701 23,667 163,139 182,508 421 0.08 0.098 0.109

Notes: The table reports the number of firms in the Annual Industrial Survey by year as well as averages of main variables by year. Monetary variables are in th CNY (CPI adjusted, in 2000 CNY). We restrict our sample to firms with annual sales above 20 million CNY (CPI adjusted, in 2000 CNY) and with non-missing data for the following monetary variables: long-term liabilities, total assets and annual sales. na: variable not available in that year.
Table 2: New loans and State Ownership, All Years
Basic Correlations in the Data

<table>
<thead>
<tr>
<th>Dep. var.: $\frac{\Delta LTliab_t}{Rev_{t-1}}$</th>
<th>old SOE policy</th>
<th>new SOE policy introduced</th>
<th>stimulus</th>
<th>post-stimulus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A (1) (2) (3) (4) (5) (6) (7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I(State Controlling Shareholder)</td>
<td>0.400***</td>
<td>-0.223***</td>
<td>-0.485***</td>
<td>-0.121***</td>
</tr>
<tr>
<td></td>
<td>[0.077]</td>
<td>[0.041]</td>
<td>[0.068]</td>
<td>[0.045]</td>
</tr>
<tr>
<td>Observations</td>
<td>39,055</td>
<td>145,181</td>
<td>72,471</td>
<td>229,073</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.049</td>
<td>0.021</td>
<td>0.028</td>
<td>0.011</td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I(State Owned Firm)</td>
<td>0.388***</td>
<td>-0.254***</td>
<td>-0.506***</td>
<td>-0.122***</td>
</tr>
<tr>
<td></td>
<td>[0.076]</td>
<td>[0.040]</td>
<td>[0.066]</td>
<td>[0.042]</td>
</tr>
<tr>
<td>Observations</td>
<td>39,055</td>
<td>145,181</td>
<td>72,471</td>
<td>229,073</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.049</td>
<td>0.021</td>
<td>0.028</td>
<td>0.011</td>
</tr>
</tbody>
</table>

year fe                                      y y y y y y y
4-digit city fe                              y y y y y y y
4-digit sector fe                            y y y y y y y
firm size control                            y y y y y y y

Notes: The unit of observation is a firm. The dependent variable is change in long term liabilities between $t$ and $t-1$ over firm total revenues in year $t-1$. $I$(State Controlling Shareholder) and $I$(State Owned Firm) are indicator functions that take value 1 if, respectively: a firm reports the State as controlling shareholder, and a firm is defined as State-Owned-Enterprise according to the Hsieh and Song (2015) definition. Firm ownership status is defined in year $t-1$, with the only exception of $I$(State Owned Firm) in years 2009 and 2010, where firm ownership status refers to 2007 (as shown in Table 1, this variable is not available in the years 2008 and 2009). Firm size control: log of average number of workers in year $t-1$. To insure comparability over time we restrict our sample to firms with annual revenues above 20 million CNY (CPI adjusted). Standard errors are clustered at the firm level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 
### Table 3: Balancedness Test

<table>
<thead>
<tr>
<th></th>
<th>Exposure to credit supply shock</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>below</td>
<td>above</td>
<td>diff</td>
<td>p-value</td>
</tr>
<tr>
<td><strong>Firm characteristics:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>size (log L)</td>
<td>5.186</td>
<td>5.202</td>
<td>0.016</td>
<td>0.001</td>
</tr>
<tr>
<td>export status</td>
<td>0.274</td>
<td>0.309</td>
<td>0.036</td>
<td>0.000</td>
</tr>
<tr>
<td>age (years)</td>
<td>11.278</td>
<td>11.332</td>
<td>0.055</td>
<td>0.195</td>
</tr>
<tr>
<td><strong>City characteristics:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log gdp per capita</td>
<td>0.152</td>
<td>0.255</td>
<td>0.103</td>
<td>0.086</td>
</tr>
<tr>
<td>share of rural population</td>
<td>0.651</td>
<td>0.669</td>
<td>0.018</td>
<td>0.241</td>
</tr>
<tr>
<td>log population density</td>
<td>5.763</td>
<td>5.603</td>
<td>-0.160</td>
<td>0.038</td>
</tr>
<tr>
<td>log population</td>
<td>5.943</td>
<td>5.677</td>
<td>-0.267</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Notes:** The table reports average firm and city characteristics by exposure to credit supply shock (below and above the median). The measure of exposure to credit supply shock refers to the stimulus years 2009 and 2010. Firm characteristics observed at \( t - 1 \), \( N = 191,234 \). City characteristics observed in 2005, \( N = 557 \).
Table 4: The Effect of Bank Credit Supply Shock on Firm Borrowing

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure to Credit Supply Shock</td>
<td>0.367***</td>
<td>0.343***</td>
<td>0.325***</td>
</tr>
<tr>
<td>[0.070]</td>
<td>[0.073]</td>
<td>[0.073]</td>
<td></td>
</tr>
<tr>
<td>size (log L)</td>
<td>-0.053***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[0.018]</td>
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<tr>
<td>export status</td>
<td>-0.105***</td>
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<td></td>
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<tr>
<td>[0.037]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age (years)</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[0.003]</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>year fe</td>
<td>y</td>
<td>y</td>
<td>y</td>
</tr>
<tr>
<td>2-digit province × year fe</td>
<td>y</td>
<td>y</td>
<td>y</td>
</tr>
<tr>
<td>4-digit industry × year fe</td>
<td>y</td>
<td>y</td>
<td>y</td>
</tr>
<tr>
<td>city initial characteristics × year fe</td>
<td>y</td>
<td>y</td>
<td>y</td>
</tr>
<tr>
<td>Observations</td>
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<td>371,123</td>
<td>371,123</td>
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<td>R-squared</td>
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Notes: Unit of observation is a firm. Dependent variable is change in long-term liabilities between year $t − 1$ and year $t$ divided by total revenues in year $t − 1$. City initial characteristics include: log gdp per capita, log population density and log population, all observed in 2005. Standard errors are clustered at the firm level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 
Table 5: Heterogeneous Effects by initial SOE presence and $\log MPK$

New Loans

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure to Credit Supply Shock</td>
<td>0.249***</td>
<td>0.210**</td>
<td>0.167**</td>
<td>0.127</td>
<td>0.466***</td>
<td>0.437***</td>
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<tr>
<td></td>
<td>[0.086]</td>
<td>[0.088]</td>
<td>[0.082]</td>
<td>[0.085]</td>
<td>[0.130]</td>
<td>[0.133]</td>
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<tr>
<td>Exposure to Credit Supply Shock $\times I$(State Owned Firm)</td>
<td>1.322**</td>
<td>1.288**</td>
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<tr>
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<td>[0.586]</td>
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<tr>
<td>Exposure to Credit Supply Shock $\times \log MPK$</td>
<td>-0.320***</td>
<td>-0.333***</td>
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<tr>
<td></td>
<td>[0.092]</td>
<td>[0.093]</td>
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<td>$I$(State Owned Firm)</td>
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<td>-16.066**</td>
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<tr>
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<td>[7.415]</td>
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<td>$\log MPK$</td>
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<td>3.950***</td>
<td>4.096***</td>
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<td>[1.173]</td>
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<tr>
<td>size (log L)</td>
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<td>-0.148***</td>
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<td>[0.045]</td>
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<td>[0.003]</td>
<td>[0.003]</td>
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<tr>
<td>year fe</td>
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<td>y</td>
<td>y</td>
<td>y</td>
<td>y</td>
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</tr>
<tr>
<td>2-digit province $\times$ year fe</td>
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<td>y</td>
<td>y</td>
<td>y</td>
<td>y</td>
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</tr>
<tr>
<td>4-digit industry $\times$ year fe</td>
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<td>y</td>
<td>y</td>
<td>y</td>
<td>y</td>
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</tr>
<tr>
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<tr>
<td>R-squared</td>
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<td>0.024</td>
<td>0.024</td>
<td>0.024</td>
<td>0.024</td>
<td>0.024</td>
</tr>
</tbody>
</table>

Notes: Unit of observation is a firm. Dependent variable is change in long-term liabilities between year $t-1$ and year $t$ divided by total revenues in year $t-1$. The variable $I$(State Owned Firm) is an indicator function equal to 1 if the firm is a SOE according to the definition proposed by Hsieh and Song (2015) and it is defined in 2007. $\log MPK$ is the natural log of industrial value added divided by book value of fixed assets, and it is defined in 2007. City initial characteristics include: log gdp per capita, log population density and log population, all observed in 2005. Standard errors are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.
### Table 6: Heterogeneous Effects by initial SOE presence and log $MPK$

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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</thead>
<tbody>
<tr>
<td>Exposure to Credit Supply Shock</td>
<td>1.580***</td>
<td>1.370***</td>
<td>1.227***</td>
<td>0.853***</td>
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<td>[1.173]</td>
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<td>age (years)</td>
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<td>0.014**</td>
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<tr>
<td>4-digit industry $\times$ year fe</td>
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<td>0.219</td>
<td>0.222</td>
<td>0.225</td>
<td>0.227</td>
</tr>
</tbody>
</table>

**Notes:** Unit of observation is a firm. Dependent variable is change in total fixed assets between year $t-1$ and year $t$ divided by total revenues in year $t-1$. The variable $I$(State Owned Firm) is an indicator function equal to 1 if the firm is a SOE according to the definition proposed by Hsieh and Song (2015) and it is defined in 2007. $\log MPK$ is the natural log of industrial value added divided by book value of fixed assets, and it is defined in 2007. City initial characteristics include: log gdpp per capita, log population density and log population, all observed in 2005. Standard errors are clustered at the firm level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 