Credit Allocation under Economic Stimulus: Evidence from China*

Lin William Cong† — Chicago Booth

Jacopo Ponticelli — Northwestern Kellogg and CEPR

Haoyu Gao — CUFE

Xiaoguang Yang — Chinese Academy of Sciences

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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 financial frictions such as implicit government bailout, favoring low-productivity state-controlled firms. Credit expansion further amplifies this effect. We investigate this mechanism in the context of China's economic stimulus plan introduced in response to the Great Recession, which triggered a large policy-driven expansion of bank credit. To this end, we match confidential loan-level data from the 19 largest Chinese banks with firm-level data from a large manufacturing survey. We document that, differently from the pre-stimulus years, this expansion of bank credit disproportionately favored state-owned firms and firms with low initial marginal capital productivity.

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†Contact Authors: Cong (will.cong@chicagobooth.edu) and Ponticelli (jacopo.ponticelli@kellogg.northwestern.edu).

1 Introduction

A large literature in macroeconomics and development 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 government on capital and labor markets (Buera and Shin 2013, King and Levine 1993).[1] Examples of this influence include directed lending by government-controlled banks, government subsidies to certain industries, or the preferential access to external finance often enjoyed 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 preferential access to external finance becomes more prominent and government intervention is more likely to occur. For example, in response to the Great Recession, governments in several countries introduced large fiscal and credit stimulus programs. Despite being praised by international organizations and economists alike, there is scarce empirical evidence on potentially unintended consequences of these programs in terms of resource allocation across firms, especially in developing economies that traditionally suffer from severe financial frictions.[2]

In this paper we study the dynamics of credit allocation across firms in China before and after the introduction of a major credit expansion program. We start by documenting a set of stylized facts. First, private firms in China were experiencing a relatively higher increase in borrowing relative to state-owned firms from 2000 to 2008. This is consistent with the gradual reallocation of capital from low to high productivity firms which is often described as an important driver of China economic transformation during the 2000s.[3] Second, this process of efficient reallocation reversed after the introduction of China's economic stimulus plan at the end of 2008. The plan had two main components. First, an increase in government spending of 4 Trillion CNY – or 12.6% of China GDP in 2008 – over two years.[4] Government spending focused on infrastructure projects and social welfare

[1]Buera 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 non-financial 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).

[2]For 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.

[3]See, in particular, Song, Storesletten, and Zilibotti (2011).

[4]The announced increase in government spending was twice as large as the American Recovery and Reinvestment Act (ARRA) as a share of the country GDP. The ARRA amounted to 5.3% of US GDP

policies, and was in large part carried out by local governments through so-called "local government financing vehicles" (LGFVs), off-balance-sheet companies set up to increase expenditure without officially running a deficit. The second component of the stimulus plan included a set of bank credit expansion policies – such as lower reserve requirements and lower benchmark lending rates.[5] In 2009 and 2010, following the introduction of these credit expansion policies, aggregate new bank loans doubled with respect to their 2008 level. We document a large increase in borrowing from manufacturing firms in response. In addition, we document that state-owned firms, which display lower marginal product of capital at the outset of the program, experienced larger increase in firm borrowing than private firms during the stimulus years.

We rationalize these stylized facts in a simple theoretical framework. Specifically, we build on Song et al. (2011) to 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. We augment their framework by explicitly modeling recessions and by accounting for implicit government bail-out of state-connected firms (and the consequent limited pleadgeability constraints that plague private firms). Because during recessions firms struggle to survive and differential access to external finance becomes more prominent, the efficient reallocation of capital from low to high-productivity firms slows down and can potentially reverse. We also show that credit expansions amplify the reversal of prior trend in factor reallocation. While China-specific stylized facts certainly motivate the model assumptions, this mechanism applies more generally to and is informative of 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's stimulus plan, consistently with the forces described in the 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 different credit demand or investment opportunities faced by firms. To this end, we use confidential loan-level data from the China Banking Regulatory Commission – which covers the 19 largest Chinese banks and 80% of the banking sector corporate lending market – to construct a measure of firm exposure to the credit supply

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in 2008.

[5] These credit expansion policies aimed, in part, at providing LGFVs with appropriate financing from the banking sector. However, they had a broader impact on the Chinese economy. At least half of the increase in credit during the stimulus years affected Chinese firms outside of LGFV-financed projects – which are mostly in the construction and utility sectors.

generated by the stimulus plan. More specifically, we exploit variation in national lending by banks with which a firm has a pre-existing relationship to construct an instrument for firm borrowing that is plausibly exogenous with respect to a firm-specific credit demand (see Chodorow-Reich (2014)). We show that our measure of credit supply indeed explains variation in firm borrowing. Next, we match loan-level data with firm-level data from the Annual Survey of Industrial Firms using unique firm identifiers. This allows us to study the heterogeneous effects of credit supply across firms with different initial ownership status (SOEs vs Private Firms) and level of productivity. In addition, this match allows us to study the effect of credit supply on real firm-level outcomes such as investment and employment.

The results obtained with this identification strategy are consistent with the simple correlations in the data and the mechanism described in our model. During the stimulus years of 2009 and 2010, the effect of credit supply on firm borrowing is larger for SOEs relative to private firms. We also show that, over the same period, the effect of credit supply on firm borrowing is larger for firms with lower initial marginal productivity of capital. This result is consistent with existing evidence that state-owned firms are, on average, less productive than private firms in China.[6] Taken together, these findings are indicative of an increase in misallocation of bank credit during the stimulus years. Crucially, we find opposite effects when applying our identification strategy to the pre-stimulus period. In the years for which both loan-level data and firm-level data are available (2006 to 2008) we find that the effect of changes in credit supply on firm borrowing were larger for private firms and for firms with higher marginal productivity of capital than for SOEs.

Next, we estimate the effect of credit supply on real firm level outcomes. On average, we find that firms experiencing larger increases in credit supply also experience larger increases in investment and employment. The effects, however, are heterogeneous between SOEs and private firms, as well as between stimulus years and non-stimulus years. In particular, we find that, outside stimulus years, private firms have a larger elasticity of investment to bank credit. This is consistent with the notion that Chinese private firms are, on average, more credit constrained than state-owned ones. On the other hand, during the stimulus years, the elasticity of firm investment to credit supply is larger for SOEs than for private firms. This is consistent with the commonly-held belief that, to contain the effects of the Global Financial Crisis, the Chinese government artificially directed state-owned firms to sustain investment, in order to temporarily boost aggregate economic activity, albeit reducing aggregate productivity for the short and intermediate

[6] Several papers have documented how state-owned firms are, on average, less productive than private firms in China. For example, Song et al. (2011) show that SOE have, on average, 9% lower profitability than private firms in the years 1998 to 2007. Similarly, Brandt, Hsieh, and Zhu (2005) find large differences between SOE and non-SOE in terms of TFP. Hsieh and Song (2015) show that the gap in marginal product of capital between SOE and non-SOE has been closing in the years between 1999 and 2007, but nonetheless find that, in 2007, "capital productivity among state-owned firms and privatized firms remained about 40 percent lower (compared to private firms)."

terms.

Another potential interpretation of our results is that the larger allocation of new credit to low-productivity, state-owned firms during the stimulus years might have had social benefits such as preserving political stability and containing unemployment. However, we find no evidence that employment at state-owned firms responded to credit supply shocks differently than their private counterparts during the stimulus years. Instead, the implied elasticity of employment to credit supply is small in magnitude and not statistically different from zero during stimulus years. It is larger and positive for both private firms and SOEs outside of stimulus years.

To extend our analysis to all firms in the Annual Industrial Survey beyond medium and large firms with access to large credit lines and borrowing relationships with the 19 major banks that the loan-level data cover, we also propose an alternative strategy that builds credit supply shock at city level instead of firm-level. As we do not directly observe bank-firm lending relationships for all firms, our measure of exposure exploits differences in lending market shares of Chinese banks across cities and is based on the geographical location of their branch network. In particular, we collect data on bank branch addresses before the stimulus years to construct a measure of initial exposure of firms located in each city to the overall lending of each bank. This alternative specification generates results that are qualitatively similar and larger in magnitude than those obtained with our main identification strategy.

Related literature

Our paper contributes to the literature in macroeconomics and development that studies misallocation and the process of reallocation of factors of production across firms. In a seminal study, Hsieh and Klenow (2009) show that misallocation of factors of production across firms can potentially explain a large fraction of the observed differences in aggregate total factor productivity and income across countries. Therefore resource reallocation across heterogeneously productive firms could contribute substantially to aggregate output (Restuccia and Rogerson (2008)). For example, Song et al. (2011) propose a model where the reallocation of capital and labor from less productive but financially integrated firms to more productive but credit-rationed firms can explain China's fast economic growth and large net foreign surplus despite a high rate of return on domestic investment. Using data on Chinese manufacturing firms, Hsieh and Song (2015) document that 83% of state-owned firms in 1998 were either shut down or privatized by 2007. They also document a convergence in labor productivity between surviving state-owned firms and private firms from 1998 to 2007. But capital productivity still remained 40% higher in private firms in 2007. In another related paper, Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015) show that, following the adoption 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.

Our paper adds to these prior studies by illustrating how financial frictions can impact the dynamics of misallocation across the business cycle and the credit cycle. In particular, to the best of our knowledge, our paper is the first to document China's reallocation reversal.[7] Conventional wisdom on the link between business cycles and resource allocation follows the Schumpeterian notion that recessions ameliorate underlying allocation of resources absent financial frictions (e.g.,Caballero, Hammour, et al. (1994), Cooper, Haltiwanger, et al. (1993), and Mortensen and Pissarides (1994)). Most studies considering financial frictions are either silent on efficient allocation of resources across firms with heterogeneous productive efficiency (e.g. Kiyotaki and Moore (1997)), or conclude that recessions are associated with cleansing (albeit excessive) of the least productive matches (e.g., Ramey and Watson (1997)). In contrast, our paper documents that recessions can increase misallocation, because financial frictions – such as easier access to finance for state-connected firms – affect resource allocation to a greater extent during recessions. This result applies whenever state-connected firms have lower marginal productivity of capital, which we think is a pattern observed also outside of China.[8]

Our paper is also related to a new wave of research that studies the drivers and consequences of China's credit boom, and in particular the large increase in debt of Chinese local governments and the rise of shadow banking. The 2008 stimulus plan encouraged the creation of LGFVs, and several recent papers have analyzed the unintended consequences of this financial liberalization. Huang, Pagano, and Panizza (2016) exploit variation in debt issuance across Chinese cities to show that public debt issuance by local governments crowded out private investment by Chinese firms. Bai, Hsieh, and Song (2016) show that local financing vehicles played an integral role in implementing the fiscal expansion of 2009 and 2010, and off-balance sheet spending by local governments took off afterward, leading to misallocation of credit towards private firms favored by local governments.[9] Closely linked to China's recent credit boom is the rise of shadow banking. Hachem and Song (2016) propose a theoretical mechanism whereby stricter liquidity regulation in the presence of asymmetric bank competition can fuel shadow banking activities and credit growth similar to the one observed in China.[10] Through an alternative mechanism

[7]To be clear, a number of papers such as Firth, Lin, Liu, and Wong (2009) and Boyreau-Debray and Wei (2005) have shown that there is misallocation in China favoring SOEs or certain strategic regions and sectors. What is new is the dynamics of reallocation driven by the stimulus package.

[8]Barlevy (2003) also argue that more efficient projects may experience worse credit constraints during recessions because more efficient firms' borrowing more, which differs from our economic channel of heterogeneous financial integration. While they focus on business cycle only, we show that credit expansion makes reallocation less efficient.

[9]Other papers studying the short and long run effects of fiscal stimulus through LGFVs include Deng, Morck, Wu, and Yeung (2015), Ouyang and Peng (2015), and Wen and Wu (2014).

[10]Higher loan-to-deposit ratio requirement introduced by the Chinese government push small banks to offer off-balance-sheet wealth management products as a form of regulatory arbitrage. Large banks

of debt rollover, Chen, He, and Liu (2017) attribute the unprecedented rapid growth of shadow banking activities in China after 2012 as one of the unintended consequences of the massive fiscal stimulus plan.[11]

Our paper focuses on an aspect so far overlooked by this recent literature. As we explain in more details in section 2, China's stimulus package involved pursuing both fiscal stimulus in the form of large government spending, and credit stimulus in the form of relaxing funding and lending constraints of traditional banks. During the stimulus years, as much credit has gone to firms directly as through the local government. The credit stimulus therefore not only facilitated financing local government spending through LGFVs, but had a broader impact on the Chinese economy, including firms outside the construction and utilities sector.

While our paper primarily draws evidence from China, the world's second largest economy, the insights apply more broadly to various credit expansions, liquidity injections, and stimulus programs around the globe. Therefore, our paper also adds to the general discussion on the efficacy and unintended consequences of intervention policy that aim at stimulating real economic activities or stabilizing financial markets, but may be hampered by market frictions.[12] Although the paper highlights the intervention's exacerbating effect on misallocation of capital across firms, our analysis does not take into account potential benefits of the stimulus program in terms of social and political stability, nor does it currently track loan performance. These are interesting topics for future work.

The rest of the paper is organized as follows. Section 2 provides the institutional background and highlights the main features of China's 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.

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respond by tightening liquidity in the inter-bank market and lending more to non-financial firms.

[11] Similarly, Archarya, Qian, and Yang (2016) analyze a proprietary panel data on bank-issued wealth management products and argue that the stimulus plan triggered shadow banking and increased fragility in the banking system. However, Wang, Wang, Wang, and Zhou (2016) contend that shadow banking as China's dual-track interest rate liberalization can lead to efficiency gain.

[12] See Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Shleifer and Vishny (2010), Stein (1998), and Kashyap and Stein (2000) for general intervention impacts, and more recently Brunnermeier, Sockin, and Xiong (2017, 2016), Hachem and Song (2016) and Acharya, Eisert, Eufinger, and Hirsch (2017). Two close examples related to bank credits are Bleck and Liu (2014) that develops a theory of sectoral misallocation under excessive liquidity injections, and 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, we focus on the dynamics of misallocation across firms.

2 Background and Stylized Facts

2.1 China Economic Stimulus Plan

The second half of 2008 saw the onset of the global recession. China, after almost 30 years of unprecedented economic growth and with a large exposure to international trade, was at risk of hard landing. To contain a potential slowdown, the Chinese government introduced a large stimulus plan – a combination of fiscal and credit programs. Figure 1 illustrate the structure of the economic stimulus plan. In what follows we describe it in detail.

The fiscal part of stimulus, officially announced on Nov 9 of 2008, prominently featured spending 4 Tr CNY (US$586 billion) over the following two years (2009 and 2010) on a wide array of national infrastructure and social welfare projects. The central government directly funded 1.18 Tr CNY – around one-third of the stimulus plan – using government budget and treasury bonds. The remaining 2.82 Tr CNY – around two-thirds of the planned investments – were expected to be financed by local governments. At the beginning of 2009, to help local governments access external financing, the central government facilitated and actively encouraged the establishment of LGFVs, off-balance sheet companies set up by local governments to finance mostly investments in public infrastructure and affordable housing projects.[13]

In parallel, the Chinese government encouraged an increase in credit supply to the real economy by banks. Traditionally, the government influences bank credit supply through setting loan quotas, deposit and lending rates, and required reserve ratios.[14] Total loan quotas, which are the lending targets for commercial banks that bank officials are encouraged to meet, were increased from $4.9 trillion CNY in 2008 to almost $10 trillion CNY in 2009. Compliance to new lending targets is usually achieved by the central bank, People's Bank of China (PBoC) through adjusting bank regulation. Part of the stimulus was therefore generated by a relaxation of bank financing constraints. Two most prominent measures are: first, in the last quarter of 2008, the PBoC lowered commercial banks' reserve requirement ratio from 17.5% to 13.5% for medium-sized and

[13]Bai et al. (2016) describe LGFVs in details: these companies are the reincarnation of the trust and investment companies of the 1990s, which helped local governments raise funds from both domestic and overseas investors. LGFVs existed before 2009 but their activities were heavily restricted for a prolonged period of time. They are typically endowed with government resources. For example, the authors note that after 2010 when LGFV borrowing requirements were tightened, LGFVs heavily utilized government land as collateral to obtain loans from banks and trusts, and increasingly financed private commercial projects after 2010.

[14]Credit supply in China has long been constrained. The 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 sufficiently to fund their loan growth while meeting this requirement. Reserve requirement ratio and interest rate regulations were also limiting banks' lending capacities.

small banks, and from 17.5% to 15.5% for large banks;[15] second, the PBoC reduced the base one-year lending rate from 7.47% to 5.31%.[16]

A significant fraction of the new bank credit went to LGFVs. As a matter of fact one of reasons behind the changes in banking regulation was exactly to meet LGFVs' borrowing needs. Chen et al. (2017) and Bai et al. (2016) estimate that the fiscal investment target not funded by the central government were largely financed by LGFVs and 90% of the increase in local government debts during the stimulus period were in the form of bank loans. However, it should be emphasized that the credit expansion had a broader impact on the economy beyond supporting LGFVs.[17] New bank credit to the real economy during the stimulus years far exceeds borrowing by LFGVs. Using a simple extrapolative model, Chen et al. (2017) estimate that in 2009 alone, abnormal bank credit to the real economy was around 4.7 trillion CNY, among which LGFVs received around 2.3 trillion, the non-residential non-LGFV sector received 1 trillion, and the residential sector received 1.4 trillion. This implies that firms operating in sectors such as manufacturing could have received during the stimulus years comparable additional external finance as construction firms and utility companies contracted or acquired by LGFVs in the same period.

In what follows we present a set of stylized facts using both aggregate and micro data consistent with the above description of the stimulus plan.

2.2 Stylized Facts with Aggregate and Firm-level Data

a) Aggregate Flow of Credit to Real Economy

We start by presenting a set of simple stylized facts on the credit stimulus using aggregate data. Figure 2 shows the flow of Aggregate Financing to the Real Economy (AFRE-F) according to Central Bank data between 2002 and 2015. The AFRE-F is divided into 5 categories: bank loans, equity financing, corporate bonds, several types of off-balance sheet lending which we group under "shadow banking", and other types of financing.[18] As shown, the annual flow of bank lending to the real economy increased from

[15] Large commercial banks refer to Bank of China (BOC), China Construction Bank (CCB), Industrial and Commercial Bank of China (ICBC), Agricultural Bank of China (ABC), and Bank of Communications (BoCom); medium-sized and small commercial banks include the remaining 12 joint-equity commercial banks, urban and rural commercial banks, and urban and rural credit unions.

[16] Banks are typically allowed to set interest rates within a pre-specified range of the base rate. Until 2014, the permissible range around the base lending rate were 90% - 110% for large banks and 90%-130% for small and medium-sized banks. To give banks an extra incentive to lend money instead of hoarding reserves, the central bank also lowered by 0.27 percentage points the interest rates that it pays banks for reserves deposited with it (`http://www.nytimes.com/2008/11/27/business/worldbusiness/27yuan.html`).

[17] At the World Economic Forum Annual Meeting of New Champions 2009 (Summer Davos), China's Premier Wen described the stimulus package as pursuing both "proactive fiscal policy and easy monetary policy" and emphasized that "Some people take a simplistic view and believe that China's stimulus package means only the four trillion CNY investment. This is a total misunderstanding."

[18] The data source is the "Total Social Financing" (TSF) dataset of the PBoC. Following Hachem and Song (2016) we define shadow banking as both loans by trust companies (trust loans) and entrusted firm-

5 to 11 Trillion CNY (or around 1 Tr USD) between 2008 and 2009. This is an increase of 7 Tr CNY with respect to the previous 5 years average, or an increase of 5.5 Tr CNY in deviation from a linear trend obtained using 2002 to 2008 data, both far exceeding the increase in LGFV borrowing.

b) Changes in Bank Regulation to Promote Bank Credit Supply

The increase in bank credit documented in Figure 2 is consistent with the measures introduced by the PBoC at the end of 2008 and described in section 2.1. First, in the fourth quarter of 2008, the Central Bank reduced required reserve ratios (RRR) for commercial banks. The rationale was that if banks are required to keep less reserves with the Central Bank, they have more liquidity available for other investments, including lending to the real economy. Figure 3 shows the evolution of mandatory RRR between 2005 and 2013. The solid lines show the mandatory RRR set by the Central Bank, while the dots show the average actual reserves as a fraction of bank deposits in each quarter observed in the data. We report these numbers separately for large, medium and small banks, as banks of different sizes are subject to different RRRs. As shown, Chinese banks tend to keep reserves as a share of their deposits close to the ratio required by the PBoC. This suggests that, for most banks, RRR is a binding constraint. As shown, banks tend to quickly adjust their reserves in reaction to variation in mandatory RRR. Therefore, the decrease in mandatory reserves observed in Q4 2008 is likely to have freed liquidity that became available for lending.

Second, the Chinese Central Bank lowered its benchmark lending rates for loans of different maturities. Benchmark rates are lower bounds on interest rates that commercial banks are allowed charge to their clients. These benchmark rates tend to be a binding from below constraint for commercial banks. This can be seen in the lower right graph of Figure 3, where we report the benchmark lending rate for loans with maturity between 6 months and 1 year. As shown, the Central Bank lowered this rate by 2 percentage points in the last quarter of 2008, from 7.47% to 5.31%. In the same graph we also show the interest rate on loans to Chinese publicly traded firms as reported in their company statements. This selected sample of loan-level data shows that (i) interest rates charged are usually close to the benchmark rate set by the Central Bank, (ii) periods in which the Central Bank lowers its benchmark rate are usually accompanied by a larger number of bank loans to publicly traded companies.

c) Credit Flow to Manufacturing Firms

We now document a set of basic stylized facts in our micro data. First, we document that firms covered in the Annual Industrial Survey display a sharp increase in long-term

to-firm loans (entrusted loans). We include bankers' acceptances in the "other" category. It is important to notice that this dataset does not include government and municipal bonds. Also, data for 2015 does not include loans to LGFVs 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.

liabilities during the years of the stimulus plan. It is important to keep in mind that, as explained in detail in section 4, this survey covers manufacturing firms and does not include construction companies.[19] The sharp increase in firm borrowing observed in 2009 and 2010 is consistent with the increase in bank credit flows to the real economy reported in Figure 2 and with the changes in banking regulation described above.

Figure 4 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 manufacturing firms with annual revenues above 20 million CNY, for which the survey is effectively a Census between 1998 and 2013. The upper graph of Figure 4 reports the sum across firms of the monetary value of long-term liabilities in each year. The lower 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 interpret long-term liabilities as composed exclusively by bank debt, Figure 4 indicates that bank credit flow to manufacturing firms increased from 70 Bn CNY in 2008 to 1.25 Trillion CNY in 2009. This is an increase of 1 Tr CNY with respect to the previous 5 years average, or an increase of 986 Bn CNY in deviation from the linear trend obtained using 2002 to 2008 data. In deviation from the linear trend, the abnormal bank credit to manufacturing firms observed in 2009 correspond to 18% of the abnormal bank credit flow to the real economy reported for the same years by the Total Social Financing Database and showed in Figure 2.

d) Credit Allocation Across Manufacturing Firms

After documenting that our data on manufacturing firms do 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:

$$\Delta y_{icjt} = \alpha_t + \alpha_c + \alpha_j + \beta C_{icjt-1} + \varepsilon_{icjt} \tag{1}$$

where the outcome variable is the change in long-term liabilities of firm i between year $t-1$ and year t (our proxy for new loans) divided by total revenues of firm i in $t-1$.[20] 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, the ownership status of firm i or its level of marginal product of capital MPK. 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

[19]See section 4 for a detailed description of the data sources and variables.

[20]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.

1998 and 2013 and estimate equation (1) separately for each sub-period. This allows us to study capital allocation separately for pre-stimulus, stimulus and post-stimulus years. 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) where C_{icjt-1} captures two different pre-determined firm characteristic: state-ownership in panel A, and log of marginal product of capital in panel B. State ownership status is an indicator function 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). We use as a proxy of marginal product of capital the average product of capital computed as industrial value added divided by book value of fixed assets.

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 being the 1998-1999 period, which pre-dates the new policy favoring the privatization of SOEs introduced by the Communist Party's Central Committee in September of 1999.[21] 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 9 we plot the estimated coefficients reported in Panel A of Table 2 along with their 95 percent confidence intervals for each sub-period.

Next, in panel B, we estimate equation (1) where C_{icjt-1} is log of marginal product of capital. The estimates show that, between 2000 and 2008, new loans were allocated relatively more towards firms with higher initial marginal product of capital. This trend is reversed during the stimulus plan years, when new credit is allocated relatively more to less productive firms.

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, and across firms with different initial marginal product of capital. However, it is important to emphasize how the estimates presented in this section cannot be interpreted as directly derived from credit supply shocks. This is because we cannot separate the effect of the stimulus or other forces affecting credit supply from credit demand forces operating contemporaneously. Before we present an identification strategy that aims at disentangling supply from demand forces in section 5, we first rationalizes the aforementioned stylized facts in the next section.

[21] For more details see Hsieh and Song (2015).

3 The Model

This section develops a dynamic model to illustrates how financial frictions affect credit allocation across firms. 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.

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 using capital from private financiers (successful, old entrepreneurs) or banks or both.

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

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

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 μ_t (success), and 0 otherwise (failure). Similarly, $\tilde{A}_{P,t} = \chi A_t$ with probability μ_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 μ_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.[22] We set N_t to be a constant to focus on the labor share dynamics and illustrate key mechanisms.[23]

A measure M_t of skilled entrepreneurs are born in each period and live for two periods, with preferences parametrized by:

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

where β 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

[22] 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".

[23] 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.

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 ϕ 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.[24] 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. We model credit expansion or contraction as exogenous unexpected shifts to Q_t that is otherwise stable.[25] The credit market is competitive and bankers rationally set lending rates to S and P firms to clear the market, consistent with empirical findings in studies such as Firth et al. (2009) that banks lend primarily based on commercial judgments.

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 η 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 π is the after-wage revenue. This *limited pledgeability friction* is absent for S firms because the state can always supply additional assets and collateral.[26] 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.[27] $\delta = \frac{\mu}{\mu + (1-\mu)b}$ captures how much S firms are differentially favored in terms of interest rates or cost of capital (the *interest rate friction*).[28]

The differential pledgeability constraints and interest rates can be thought as reflecting several real world frictions commonly observed in emerging economies transitioning to

[24]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, ϕ could be a bargaining outcome, or determined by agency frictions as described in Song et al. (2011).

[25]In reality, Q_t is time-varying post-stimulus and the stimulus could have been anticipated. This is not crucial to our results.

[26]We can alternatively set $\eta = 1$ for S firms and show in equilibrium the constraint does not bind.

[27]Implicit bailout is also the driver in Chang, Liu, Spiegel, Zhang, et al. (2017), in which the government provides guarantees on bank loans to SOEs, effectively making them risk-free. Lenient rollovers and conversion of bad loans into equities are also common.

[28]A revealing example of selective bail-out by the Chinese government is the case of China Eastern and East Star Airlines. The former is a state-owned enterprise while the latter is privately owned. Both airlines were in financial distress at the beginning of 2009. China Eastern obtained a capital injection of 7 billion CNY from the State-owned Assets Supervision and Administration Commission of the State Council (SASAC). East Star Airlines, on the other hand, could not raise new capital and was declared bankrupt in August 2009.

market-based systems but where state influences still linger (Shleifer and Vishny 1994; Wang et al. 2016; Song et al. 2011). 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;[29] (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.[30] 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.[31]

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, δ 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.[32]

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 (Brandt and Zhu (2000); Song et al. (2011)). (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.[33]

[29] They 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.

[30] The 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.

[31] The two frictions are not time-varying in the model, to be consistent with the fact that government support for SOEs did not change drastically during the episode, as least not so relative to the magnitude of the stimulus.

[32] According 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.

[33] We 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:

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

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

$$\mu(1-\phi)(k_P^\alpha (\chi A n_P)^{1-\alpha} - R_{P_t} l_P - w n_P),$$

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

$$\phi[k_P^\alpha (\chi A n_P)^{1-\alpha} - R_P l_P - w n_P].$$

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:

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

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

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

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

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

The entrepreneur's lifetime utility maximization problem, conditional on initial success and subject to limited pledgeability is:

$$
\begin{aligned}
& \max_{c_1,c_2} \frac{c_1^{1-\frac{1}{\theta}}-1}{1-\frac{1}{\theta}} + \beta\frac{c_2^{1-\frac{1}{\theta}}-1}{1-\frac{1}{\theta}} \\
\textit{with} \quad & c_1 = m_1 - \frac{s_{P,2}}{\mu_1}, \\
\textit{and} \quad & c_2 = \mu_2\frac{(1-\phi)(\rho_2(l_{P,2}+s_{P,2})-R_{P,2}l_{P,2})}{\mu_1}, \\
\textit{subject to} \quad & R_{P,2}l_{P,2} \leq \eta\rho_2(s_{P,2}+l_{P,2}),
\end{aligned}
$$

where $m_t = (1-\eta B_t)\rho_t k_t$ is his or her total payoff in period t, and B_t is an indicator of whether the pleadgeability constraint is binding in period t. 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, the pledgeability constraint could become non-binding if $\delta\chi^{\frac{1-\alpha}{\alpha}} < 1$, and P firms stop borrowing.[34] In either case, there is a unique optimizer

$$
s^*_{P,t} = \left(1+\beta^{-\theta}((1-\phi)\psi_t)^{1-\theta}\right)^{-1}\mu_{t-1}m_{t-1},
$$

where

$$
\psi_t = \rho_t\mu_t\left(1-B_t+B_t\frac{(1-\eta)R_{P,t}}{R_{P,t}-\eta\rho_t}\right),
$$

can be interpreted as the private capital productivity.

The equilibrium can then be solved in closed-form using the market clearing conditions:

$$
\underbrace{Q_t}_{\text{Credit Supply}} = \underbrace{l_{S_t}+l_{P_t}}_{\text{Credit Supply}} = \underbrace{k_{P,t}+k_{S,t}-s_{P,t}}_{\text{Credit Demand}} \tag{2}
$$

$$
N_t = n_{P,t}+n_{S,t} = \frac{\chi^{\frac{1-\alpha}{\alpha}}k_{P,t}+k_{S,t}}{A_t}\left(\frac{R_{S,t}}{\alpha}\right)^{\frac{1}{1-\alpha}} \tag{3}
$$

3.3 Discussion and Implications

Reallocation of Capital and Labor

We first examine the dynamics of factor reallocation. The growth rate of P firms in capital and labor share is driven by

$$
\begin{aligned}
1+\gamma_t = \frac{k_{P,t}}{k_{P,t-1}} &= \frac{\psi_t}{(1-\eta B_t)\rho_t\mu_t}\frac{s^*_{P,t}}{k_{P,t-1}} \\
&= \phi\frac{\mu_{t-1}\rho_{t-1}}{\mu_t\rho_t}\tilde{\psi}_t\left(1+\beta^{-\theta}((1-\phi)\psi_t)^{1-\theta}\right)^{-1}
\end{aligned} \tag{4}
$$

[34] Because μ goes down in a recession, making this a more likely scenario.

where $\tilde{\psi}_t = \frac{1-\eta B_{t-1}}{1-\eta B_t}\psi_t$. 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 define the aggregate TFP through equating the total output under the same production function,

$$\begin{aligned} TFP_t(Q_t + s_{P,t})^\alpha N_t^{1-\alpha} &= k_{S,t}^\alpha (A_t n_{S,t})^{1-\alpha} + (Q_t + s_{P,t} - k_{S,t})^\alpha [\chi A_t (N_t - n_{S,t})]^{1-\alpha} \\ TFP_t &\propto \lambda_{k,t}^\alpha \lambda_{n,t}^{1-\alpha} + \chi^{1-\alpha}(1-\lambda_{k,t})^\alpha (1-\lambda_{n,t})^{1-\alpha}, \end{aligned}$$

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

$$d_t = \frac{\lambda_{k,t}^\alpha \lambda_{n,t}^{1-\alpha}}{(1-\lambda_{k,t})^\alpha (1-\lambda_{n,t})^{1-\alpha}}, \tag{5}$$

which ranges from 0 (efficient allocation) to ∞ (least efficient allocation).[35] Figure 6 displays this distortion over time using firm-level data from the Annual Industrial Survey in the years 1998 to 2013.

Stimulus and Recession

We now discuss how the stimulus and recession affect the transition dynamics. At time t, ρ_{t-1} is already determined. Decompose (4) into $\phi(1+\beta^{-\theta}((1-\phi)\psi_t)^{1-\theta})^{-1}\rho_{P,t-1}$ which is increasing in ψ (because $\theta > 1$), and $\frac{\tilde{\psi}_t}{\rho_t}$ which is increasing in μ, and η, decreasing in b, and independent on Q.

First, we note that $\frac{\partial(1+\gamma_t)}{\partial Q} < 0$. It may seem counter-intuitive that a relaxation of financial constraint (increasing credit supply) does not benefit the more constrained P firms more. To understand this, note that an increase in Q will cause $R_{S,t}$ to fall, then

[35] First-order conditions from optimizing the TFP give two alternative indicators for misallocation: the differential marginal productivity of capital and labor (MPK and MPL) between S and P firms. The intuition is that under diminishing returns to scale, resources should be allocated preferentially to the firm with higher marginal productivity in capital or labor.In reality, firm productivity and funding friction are generally not binary, and the technology parameter A would evolve differently for different firms. Nevertheless the intuition of examining the dispersion in the marginal productivity still applies, and the difference of marginal productivity between SOE and non-SOEs after controlling for other firm characteristics constitutes a proxy for misallocation.

ψ_t (which reflects private capital productivity) decreases through a general equilibrium effect, which leads to a decrease in future private investment s.[36]. At the same time, however, $\frac{\psi_t}{\rho_t}$ (which is related to whether the pledgeability constraint is binding) does not change. This means that P firms' pledgeability constraint is not directly mitigated by increasing the aggregate credit supply. Therefore, overall γ_t decreases – 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.[37] Similarly, we note $\frac{\partial(1+\gamma_t)}{\partial\mu} > 0$ because ψ and $\frac{\tilde{\psi}_t}{\rho_t}$ are both increasing in μ. An economic downturn also slows down the reallocation process by limiting the saving and private investing 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.[38] Moreover, the cross partial $\frac{\partial^2(1+\gamma_t)}{\partial\mu\partial Q}$ is 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). Intuitively, differential treatment of S and P firms matters more during recessions because P firms find it hard to rely only on private capital (whose growth is slow during recessions). We illustrate these predictions of the model in terms of credit share of S firms in Figure 7 (capital and labor shares are similar). The upper panel shows the case in which the economy experiences a permanent change ($T = 8$) in credit supply (higher Q) and deterioration of economic environment (lower μ). The lower panel shows the case in which the economy experiences a temporary change 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. The figure also shows that both recession and credit expansion can slow down or reserve the efficient reallocation, and credit expansion during recession exacerbates the reversal.

Both Figure 6 and Figure 8 show the model predictions well capture stylized facts observed in the data. Figure 8 reports the share of SOE in: total number of firms, total revenues, total long-term liabilities and total book value of physical capital. As shown,

[36]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. The general equilibrium effect thus leads to the credit expansion disproportionally supporting S firms, and slows down the reallocation of resources to P firms, regardless of the economic condition and whether the pledgeability constraint is binding.

[37]In a related study, Chang et al. (2017) discuss in a DSGE model how RRR adjustments impact capital reallocation and macroeconomic stability. Their findings complement ours in that increasing RRR leads to reallocation of credit from SOE firms to private firms.

[38]This slow-down of the reallocation process can also be obtained in the original model in Song et al. (2011) by exogenously lowering interest rates. However, we need the additional assumption that the pledgeability constraint is always binding.

the share of SOEs has been increasing in all these dimensions starting from the stimulus years, reversing the prior trend. The reversal is particularly strong for the SOE share in long-term liabilities and physical capital, which almost reversed to their early 2000s levels.

Financial Frictions

Let us examine the role of financial frictions. Both limited pledgeability and interest rate frictions control the speed of growth of P firms relative to S firms. The two have interesting interactions. When interest rate distortion is severe (small δ), the two are substitutes and limited pledgeability stops binding (P firm no longer borrows). When the interest rate distortion is small (large δ), the two frictions are complements and together may restrict P firms' growth further. Both frictions are thus realistic and in combination reflects differential access to credit by S and P firms.

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 η or reducing b (same as increasing δ and fixing μ) drives up R_S when pledgeability constraint is binding. All these in turn leads to higher ψ. 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

$$\chi > \left[\frac{1-\delta+\alpha\delta-\alpha\delta\eta}{\alpha\delta+\delta\eta-\alpha\delta\eta-\delta^2\eta}\right]^{\frac{\alpha}{1-\alpha}} \tag{6}$$

which still satisfies $\eta\delta\chi^{\frac{1-\alpha}{\alpha}} < 1$ (pledgeability constraint binding).

Interest rates are exogenous in Song et al. (2011), and relaxing the pledgeability constraint always facilitates the reallocation of resources from less productive firms to more productive firms. Equation (4), however, is increasing in ψ_t, which can be increasing in η if and only if $\delta\chi^{\frac{1-\alpha}{\alpha}} > 1$. Hence we see that in addition to directly contributing to the misallocation of credits, δ plays an important role in that it relaxes the pledgeability constraint and once $\delta < \chi^{\frac{\alpha-1}{\alpha}}$, increasing η 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 adds more realism, but also illustrates 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 understand the long-term impact, we derive the steady states of the economy. Rewriting the steady states (SS) of equation ((4)),

$$\phi\psi(1+\beta^{-\theta}((1-\phi)\psi)^{1-\theta})^{-1}-1=0 \tag{7}$$

Denote the unique positive solution by ψ_0.

Inverting the definition of ψ, 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 equations (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 reallocation, 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 μ 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 μ is small. In this case,

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

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 μ. Therefore, when Q increases or μ decreases, s_P falls, so does l_P (loans borrowed) and k_P, n_P. Economic recession and credit expansion have long-term impacts. Cross partial in Q and μ 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 η 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 two main data sources used in this paper are the China Banking Regulatory Commission (CBRC) Loan Level database and the Annual Survey of Industrial Firms of the China's National Bureau of Statistics. Additionally, we use data on bank branch location from the CBRC. In what follows we describe in detail each of these datasets.

The CBRC loan-level database covers loan-level data from 19 of the largest Chinese banks. The data is collected monthly by the CBRC. Banks are required to transmit to the regulator information on all loans to borrowers whose annual outstanding loan balance with a given bank is equal or above 50 million RMB. The original data comes at monthly level and covers the period between October of 2006 and June of 2013. The dataset reports loan-level characteristics such as loan amount, maturity, issuing date and repayment information. In terms of coverage, the CBRC data covers around 80% of total oustanding loans to Chinese companies, which correspond to around 50% of overall bank lending as reported in the Total Social Financing dataset and shown in Figure 2. Crucially, the dataset reports both bank and firm unique identifiers, which allows us to match loan-level data with firm-level data for the manufacturing firms covered in the Annual Survey of Industrial Firms.

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.[39] 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 net increase in bank loans, 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

[39] 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.

firms that respond to the Hsieh and Song (2015) definition of SOE. As shown, all these measures of state control have 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. This data report the exact address of all bank branches operating in mainland China, Hong Kong and Macao. As explained in section 5, we use use the address of each branch to construct bank specific proxies for the share of their aggregate corporate lending allocated to different cities. We define cities as the second 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, our pre-stimulus baseline year. Figure 5 shows the geographical distribution of bank branches in our dataset in 2005 (upper-left graph) as well as the geographical distribution of branches of three banks in our sample (Bank of China, CITIC Bank and Huishang Bank) as illustrative examples.[40]

5 Identification Strategy

In this section we describe our identification strategy. Our objective is twofold. First, to study the effect of the large credit supply increase during stimulus years on firm borrowing, investment and size. Second, to study how the larger credit supply by Chinese banks was allocated across firms, with particular attention to heterogeneous effects between state-owned and private firms. The main identification challenge we face is to isolate changes in firm borrowing that are solely driven by credit supply forces from those driven by demand or investment opportunities.

In what follows we propose a measure of firm exposure to the credit supply changes generated by the stimulus plan. Similarly to Chodorow-Reich (2014), our identification strategy exploits 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.[41] To this end, we construct the following measure of firm-level exposure to bank loan supply:

$$\Delta \widetilde{L_{it}} = \sum_{b \in O_i} \omega_{bi,t=0} \times \Delta \log L_{b-i,t} \tag{8}$$

where b, i, and t index banks, firms, and time respectively. The variable $\Delta \log L_{b-i,t}$ is the change in the logarithm of the aggregate loan balance of bank b between year $t-1$

[40]Our data covers mainland China, Hong Kong, and Macao.

[41]This strategy is similar to a Bartik instrument (Bartik 1991) 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.

and t to all borrowers other than firm i. The weights $\omega_{bi,t=0}$ capture the strength of the relationship between firm i and bank b in the initial period.[42] We define the weights as $\omega_{bi,t=0} = \frac{l_{bi,t=0}}{\sum_{b \in O_i} l_{bi,t=0}}$, i.e. outstanding loans of bank b to firm i divided by total outstanding loans to firm i from all banks with which firm i has a credit relationship (the set O_i), both observed in the initial period.

In words, equation (8) uses variation in national lending by banks with which firm i had a pre-existing credit relationship to construct an instrument for firm i borrowing that is plausibly exogenous with respect to firm i specific credit demand. This type of identification strategy relies on two main assumptions.[43] 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 $\Delta \widetilde{L_{it}}$ should not explain variation in actual firm lending. The second assumption is that the cross-sectional variation in bank lending during the stimulus years reflects only supply forces or observable borrowers' characteristics, but it is uncorrelated with unobservable borrowers' characteristics that affect their credit demand. In what follows we discuss this second identification assumption in more detail.

5.1 Discussion of Identification Assumptions

For our identification strategy to be valid, a key assumption is that cross-sectional differences in aggregate lending across banks during the stimulus years are driven by differential bank exposure to the stimulus-specific changes in bank regulation, but uncorrelated with unobserved firm characteristics that affected credit demand and real outcomes during the same period. Empirically, we observe large variation across banks in the increase in corporate lending during the stimulus years. Figure 10 shows the distribution of the percentage change in average bank lending between 2007-08 and the stimulus years 2009-10. Only 8 out of 77 banks in our sample experienced a negative percentage change in lending in this period, with the median bank experiencing a 48% increase and 13 banks doubling their level of lending in 2009-2010 with respect to 2007-2008. These differences can be driven by differential bank exposure to the stimulus-specific policies described in section 2 such as lower reserve requirements and benchmark lending rates. In addition, these differences can be driven by changes in credit demand from their borrowers.

To mitigate this concern, in our empirical analysis we show that our estimates are stable to adding a set of controls including borrowers' observable characteristics. For example, it is possible that banks that responded less to stimulus policies were those

[42] In the empirical analysis we define the year $t = 0$ as the first year at the beginning of each sub-period in the data. That is: t = 2006 for the years 2007 and 2008, t=2008 for the years 2009 and 2010, t=2010 for the years 2011 to 2013.

[43] These are key assumptions in all papers that exploit pre-existing banking relationships to study the effect of changes in credit supply at bank level on firm level outcomes. See, for example, the discussions in Greenstone et al. (2015) and Chodorow-Reich (2014).

lending to industries that suffered more in the 2009-2010 period. We therefore add to our specification industry fixed effects. We also use information on value of exports at firm level to control for firm-exposure to change in global demand. Additionally, we control for province fixed effects to capture policies that specifically target certain provinces in this period, such as the large federal transfers to the Sichuan region after the 2008 earthquake. Finally, we control for standard borrower characteristic such as age and firm size.

Table 3 reports the coefficient on $\Delta \log L_{b-i,t}$ when the outcome variable is lending of bank b to firm i. As shown in column 1 and 2, the point estimates of this coefficient are stable in magnitude and precisely estimated when adding the set of observable borrower characteristics described above. This applies both when focusing on all years for which loan-level data is available (columns 1 and 2), or when focusing on the stimulus years (columns 6 and 7).

Next, we exploit the loan-level nature of the data to test whether unobservable borrowers' characteristics are correlated across borrowers of the same lender. Our main concern is that banks experiencing larger increase in aggregate lending during the stimulus years tend to serve a set of borrowers that experienced larger increase in credit demand during the same period. To this end, following Khwaja and Mian (2008), we estimate the following equation at bank-firm level:

$$\Delta\log l_{ibt} \quad = \quad \alpha + \alpha_{it} + \beta \Delta \log L_{b-i,t} + \varepsilon_{ibt} \qquad (9)$$

Where the outcome variable $\Delta\log l_{ibt}$ is the change in outstanding loan balance of firm i from bank b, and α_{it} are firm fixed effects interacted with year fixed effects, which fully absorb any firm-specific credit demand shock. The coefficient β in equation 9 is therefore solely identified by variation across lenders within the same firm. A positive coefficient implies that banks that increased their aggregate lending by more relative to other banks also increased their lending by more to the same firm. By construction, this equation can only be estimated using firms with multiple bank relationships.

The results of estimating equation (9) are also reported in Table 3. Column 5 reports the results using all years for which loan-level data is available (2006 to 2013), while column 10 reports the results when focusing on the stimulus years 2009 and 2010. As shown, the estimated coefficients on $\Delta \log L_{b-i,t}$ in both time periods are positive. Importantly, these estimates are of similar magnitude as the ones described above and obtained with the same specification but without the interaction of firm and time fixed effects. This is shown in columns 3 and 4 for the specification estimated on all years, and columns 8 and 9 for the stimulus years, and always conditioning the sample to the same set of firms borrowing from multiple lenders used to estimate equation 9. Under certain assumptions, the difference in point estimates between specifications that include firm fixed effects and those that do not captures the size of the bias induced by endogenous matching between firms and banks.[44] Therefore, the coefficients reported in Table 3 support the validity of our identification strategy.

5.2 Additional Specification: City-level Exposure

Notice that the identification strategy described above can be used to study the effect of credit supply changes on firms with pre-existing banking relationships and that are covered in the CBRC loan-level database. In that sense, this strategy focuses on the intensive margin of the credit stimulus plan. In addition, despite the CBRC loan-level data covers the majority of bank loans tomanufacturing firms in terms of loan value, they primarily include medium to large firms with access to relatively large credit lines and banking relationships with the aforementioned 19 major banks. To extend the analysis to all firms covered by the Annual Industrial Survey and potentially taking loans from other banks, we propose an alternative strategy that builds a credit supply shock at city level and . We discuss in detail in the Appendix A1 what assumptions validate this identification strategy.

Because the Annual Industrial Survey contains information on total firm-level debt, but does not contain information on specific bank-firm relationships, this alternative strategy utilizes firm-level borrowing and bank-level lending. Correspondingly, we modify equation (8) as follows:

$$\widetilde{l_{ct}} = \sum_b \omega_{bc,t=0} \times \Delta Loans_{b,t} \tag{10}$$

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. We define this measure in 2005, in the pre-stimulus period, to avoid endogenous branch openings in areas more affected by the stimulus 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.

This identification strategy relies on stronger assumptions with respect to those discussed in section 5.1. We discuss in detail these assumptions in Appendix $A.1$, where we write down a simple model of credit demand and supply as in Greenstone et al. (2015). In particular, we show that under the strong assumption that credit demand shocks are highly correlated across cities within the same province, we can fully capture sector-specific and location-specific credit demand shocks in the following model relating actual borrowing of firm i to its exposure to national level changes in bank lending

[44] This is true under certain assumptions regarding the functional form of the underlying model describing borrowing of firm i from bank b (Khwaja and Mian (2008) and Chodorow-Reich (2014)). In particular, in this model, bank exposure and firm characteristics have to be additively separable.

$$\log l_{icjt} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \log \widetilde{l_{ct}} + \varepsilon_{icjt} \tag{11}$$

As discussed in more detail in the Appendix, this strategy relies on credit demand shocks being highly correlated across cities in the same province, which may be violated. For example, Table A1 reports a balancedness test in which we see that the correlation between city-level exposure to credit supply increases during the stimulus years and initial city characteristics. Cities with larger exposure to credit supply used to have around 10% higher GDP per capita in the pre-stimulus period. 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 changes in credit supply. To partially address this concern, we add to equation 11 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 changes during stimulus years: GDP per capita, population and population density. We also control for observable firm characteristics that can affect credit demand such as firms size, age and export status. The final equation to be estimated is reported below:

$$\Delta y_{icjt} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \log \widetilde{l_{ct}} + \gamma X_{i,t-1} + Z_{c,t=0} \times \alpha_t + \varepsilon_{icjt} \tag{12}$$

where $X_{i,t-1}$ are firm-level controls and $Z_{c,t=0}$ are city characteristics observed in 2005.

6 Empirical results

In section 2.2, 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. The objective of this section is to use the identification strategy proposed in section 5 to plausibly identify the effect of changes in credit supply on firm level outcomes.

6.1 The Effect of Credit Supply on Firm Borrowing

Average Effect

We start by studying the effect of credit supply shocks on firm borrowing during the stimulus years of 2009 and 2010. The baseline equation that we estimate is as follows:

$$\Delta\log l_{ijpt} = \alpha + \alpha_j + \alpha_p + \alpha_t + \beta\Delta\widetilde{L_{it}} + \gamma X_{i,t-1} + \varepsilon_{ijpt} \tag{13}$$

where $\Delta\log l_{ijpt}$ is the change between year $t-1$ and year t in the logarithm of the outstanding loan balance of firm i, operating in industry j and province p. Notice that in this firm-level specification, the outcome variable is obtained by summing loan balance across all lenders of firm i in a given year. The coefficient of interest is β, which captures the effect of bank credit supply on firm-level borrowing. The variable $\Delta\widetilde{L_{it}}$ is defined as described in equation (8).

The estimated coefficients reported in Table 4 show that firms with larger exposure to bank credit supply experienced a larger increase in borrowing. In terms of magnitude, the estimated coefficient in column 1 indicates that a 1 percent increase in credit supply from pre-existing lenders translate into around 0.8 percent increase in firm borrowing. In column 2 we include industry and province fixed effects, as well as a full set of borrower characteristics such as firm size, age and export status. Both magnitude and precision of the estimated coefficient are stable to adding this set of borrower characteristics.

The results reported in columns 1 and 2 of Table 4 show that our measure of credit supply is a good predictor of firm borrowing.

Heterogeneous Effects

Next, we study in more detail the allocation of bank loans across firms during the stimulus years 2009 and 2010. To this end, we estimate the following version of equation (13):

$$\begin{aligned}\Delta\log l_{ijpt} &= \alpha + \alpha_j + \alpha_p + \alpha_t + \beta_1\Delta\widetilde{L_{it}} \times C_{i,t-1} + \beta_2\Delta\widetilde{L_{it}} + \beta_3 C_{i,t-1} \\ &+ \gamma X_{i,t-1} + \varepsilon_{ijpt}\end{aligned} \tag{14}$$

where the variable $C_{i,t-1}$ 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 β_1, which captures the differential effect of exposure to bank credit supply 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.[45]

Table 4 reports the results of estimating equation (14) when the outcome variable is the change in the logarithm of the outstanding loan balance of firm i between year $t-1$ and year t. In columns 3 and 4, we report the results when C_{icjt-1} captures state-ownership of firm i. The estimated coefficient β_1 is positive and significant in both specifications. This indicates that the effect of credit supply on firm borrowing is relatively larger for state-owned firms relative to private firms during the stimulus years. The estimated coefficient β_2 is also positive and significant, 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. Taken together, the magnitudes of the estimated β_1 and β_2 coefficients in column 4 indicate that, in response to a 1 standard deviation change in credit supply, state-owned firms experience an 11 percent increase in borrowing, versus the 9 percent increase for private firms.[46]

Next, in column 5 and 6, we report the results of estimating equation (14) when C_{icjt-1} is equal to the firm-level average product of capital in year 2007. Average product of capital is defined as the logarithm of industrial value added divided by book value of fixed assets and – under certain assumptions – can be used as a proxy for marginal product of capital. [47]

The estimated coefficient on the interaction between our measure of changes in credit supply and initial marginal product of capital is negative and precisely estimated. This indicates that, during the stimulus years, the effect of credit supply on firm borrowing is relatively larger for firms with lower initial marginal product of capital. The magnitude of the estimated coefficient β_1 indicates that firms with a 1 standard deviation larger MPK experienced a 8 percent lower increase in bank loans 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 respect to private firms.

Allocation Dynamics

Finally, we test whether these heterogeneous effects of credit supply on firm borrowing between SOE and private firms are specific of the stimulus plan years or a more general feature of the Chinese banking sector. To this end, we estimate equation 14 separately for three different periods: pre-stimulus years 2006 to 2008, stimulus years 2009 and 2010,

[45] As discussed in the section 4 and showed in Table 1, the variable I(State Owned Firm) is not available in the years 2008 and 2009.

[46] An important caveat is in order in reading these results. Our data does not cover entrusted loans that Chinese firms can make to each other. For example, if SOE firms in this period were lending to private firms through entrusted loans, our heterogeneous effects would be at least in part mitigated.

[47] In particular, the underlying assumptions are identical labor share and mark-ups within a given sector.

and post stimulus years 2011 to 2013. Table 5 reports the results. As shown in column 1, the coefficient on the interaction between our measure of changes in credit supply and state-ownership is negative and significant in the pre-stimulus years. This indicates that, up to the introduction of the stimulus, higher credit supply had a larger effect on firm borrowing for private firms relative to state-owned firms. In the same period, the coefficient on the interaction between changes in credit supply and marginal product of capital is positive and significant. This is consistent with the process of capital reallocation from low-productivity SOEs to high-productivity private firms that has been described as one of the sources of China's growth up to the end of 2008. As shown in columns 3 and 4, during the stimulus years the coefficients on both interactions change sign. That is, credit supply has a larger effect on borrowing for state-owned and low marginal productivity firms. Notice that this effect does not seem to persist in the post-stimulus period.

6.2 The Effect of Credit Supply on Investment and Employment

In this section we study the effect of bank credit supply on real outcomes at firm level. In particular, we focus on two outcomes: firm investment measured as change in total fixed assets divided by total assets in the previous period, and firm employment measured as the logarithm of the average number of workers. Table 6 reports the results of estimating equation (13) with these two outcomes. On average, we find that firms experiencing larger increases in credit supply also experience larger increases in investment and employment. That is, firms with higher loan supply not only experience larger borrowing, but they also invest more and hire more workers. We can use the estimates reported in Tables 6 to compute the implied elasticity of investment and employment to bank credit for Chinese firms in the period 2007 to 2013. The estimated coefficients indicate that the elasticity of firm investment to bank credit is .09. This implies that a 1 percent increase in credit supply translates into around .1 percentage points higher investment as a share of assets.[48] Similarly, the implied elasticity of firm employment to bank credit supply is .08, that is: a 1 percent increase in credit supply translates into around .08 percent increase in the number of workers.

These effects, however, are heterogeneous between SOEs and private firms, as well as between stimulus years and non-stimulus years. In particular, when focusing on all years in our sample, we find that private firms have a larger elasticity of investment to bank credit. This is consistent with the notion that Chinese private firms are, on average, more credit constrained than state-owned ones. On the other hand, during the stimulus years, the elasticity of firm investment to credit supply is larger for SOEs than for private firms. This is consistent with the commonly-held belief that, to contain the effects of the Global

[48]This elasticity is obtained by dividing the coefficient on $\Delta \widetilde{L_{it}}$ when the outcome variable is firm investment (column 1 of Table 6) by the coefficient on $\Delta \widetilde{L_{it}}$ when the outcome variable is firm borrowing (this estimated coefficient, not reported in Table 6, is equal to 1.151 and strongly significant).

Financial Crisis, the Chinese government artificially directed state-owned firms to sustain investment, in order to temporarily boost aggregate economic activity, albeit reducing aggregate productivity for the short and intermediate terms.

In terms of employment, the point estimates on the effect of credit supply are positive for both SOEs and private firms when using data for all years in our sample. However, standard errors are too large for them to be different from zero at standard statistical confidence levels. On the other hand, the elasticity of employment to credit supply is close to zero in magnitude and not statistically significant during stimulus years. This is a particularly interesting result given that larger allocation of new credit to low-productivity, state-owned firms during the stimulus years could be potentially justified for its positive social effects in terms of preserving political stability and containing unemployment. As shown, we find no evidence that employment at state-owned firms responded to credit supply changes differently than their private counterparts during the stimulus years.

6.3 Additional Empirical Results: City-level Exposure

The empirical results presented so far focus on medium to large manufacturing firms with access to relative large credit lines and that have a banking relationship with the 19 major Chinese banks covered in the CBRC loan-level dataset. In section 5.2 we presented an alternative strategy that uses a city-level measure of exposure to credit supply increases during the stimulus years. Despite this strategy relies on stronger assumptions than the identification behind the results presented above, it allows us to extend the analysis to all firms covered by the Annual Industrial Survey. In this section we report the results obtained using this alternative identification strategy.

We start by testing the effect of city-level exposure to credit supply increases on firm borrowing. The baseline specification that we estimate is described by equation 15, which we report here for convenience:

$$\Delta y_{icjt} = \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \log \widetilde{l_{ct}} + \gamma X_{i,t-1} + Z_{c,t=0} \times \alpha_t + \varepsilon_{icjt} \tag{15}$$

The coefficient of interest is β, that capture the effect of bank credit supply shock in a given city and year on changes in firm-level outcomes. 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.

Table A2 reports the results of estimating equation (15) when the outcome variable is the change in long-term liabilities between year $t-1$ and year t, divided by revenues in year $t-1$.[49] The estimated coefficients reported in Table A2 show that firms located in cities with larger exposure to bank credit supply increases experienced a larger increase

[49] All monetary variables are CPI adjusted.

in borrowing. In column 1 we estimate equation (13) including year fixed effects, as well as province and sector fixed effects interacted with year fixed effects. In column 2 we estimate the full specification showed in equation 15, including firm-level controls. As shown, the size of the estimated coefficient on the bank credit supply shock is stable and precisely estimated across specifications.

Next, we study the allocation of credit 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):

$$\begin{aligned}\Delta y_{icjt} &= \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta_1 \log \widetilde{l_{ct}} \times C_{icjt-1} + \beta_2 \log \widetilde{l_{ct}} + \beta_3 C_{icjt-1} \\ &+ \gamma X_{i,t-1} + Z_{c,t=0} \times \alpha_t + \varepsilon_{icjt}, \end{aligned} \tag{16}$$

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 β_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.[50]

Table A2, columns 3 to 6, reports the results obtained estimating equation (16) 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 estimating equation (16) when C_{icjt-1} captures state-ownership of firm i. The estimated coefficient β_1 is positive and significant in both specifications, as shown in columns 3 and 4. 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 β_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. Notice also that the magnitude of the estimated β_2 is smaller in size with respect to columns 1 and 2. Taken together, the magnitudes of the estimated β_1 and β_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

[50] As discussed in the section 4 and showed in Table 1, the variable I(State Owned Firm) is not available in the years 2008 and 2009.

10 times larger for state-owned firms than for private firms during the stimulus years.

Finally, in column 5 and 6 of Table A2, we report the results of estimating equation (16) when C_{icjt-1} is equal to the firm-level average product of capital in year 2007. 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 β_1 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.

Overall, the results presented in this section are qualitatively equivalent to those obtained using loan-level data and presented in section 6.1. In terms of magnitude, the results obtained with this alternative identification strategy are smaller, but still significant.

One major challenge in disentangling demand from supply forces in this alternative identification strategy is that we cannot account for potentially different demand shocks experienced by state-owned and non-state-owned firms that operate in the same province and narrowly defined sector. One alternative explanation for the results presented in Table A2, for example, is that state-owned firms were directly required by the central government to increase credit demand in order to expand investment in infrastructure and construction. As we already mentioned, the firm-level survey used in our paper focuses exclusively on manufacturing firms that should not be affected, at least directly, by this type of policies. However, some state-owned manufacturing firms might have received a higher demand shock than private firms operating in the same sector and province because they are input providers of other state-owned firms operating in the construction and utilities sector. For example, if state-owned construction companies were more likely to buy inputs from state-owned steel companies, this increase in public expenditure in the construction sector would generate an asymmetric demand shock for state-owned versus non-state-owned firms.

To rule out this mechanism, we show that the heterogeneous effects across SOE and non-SOE to the credit supply shock showed in Table A2 are not driven by firms operating in sectors that are direct input supplier to the construction and utilities sectors. To identify main input suppliers we use the OECD Input-Output Tables for China.[51] The

[51] More specifically, we use the OECD 2-digit industry by industry input-output table for China for the year 2002. We rank 2-digit industries that are major input providers of the construction and utilities sector based on a Leontief Inverse Matrix. For example, in the case of construction, this matrix reports the implied increase in output in each sector for a unit increase in final demand from the construction sector.

main input suppliers for the construction sector are industries in the basic metal production, which include smelting and pressing of ferrous metals – such as iron and steel – and non-ferrous metals. The main input suppliers for the utilities sector are instead industries operating in mining and quarrying, which include: coal mining and dressing, petroleum and natural gas extraction, mining and dressing of ferrous and non-ferrous metals, non-metal ores and other mining industries.

Table A3 reports the results of estimating equation (16) for the same outcomes as Table A2, but excluding firms operating in the Basic Metals production sectors (columns 1 and 2) and in the Mining and Quarrying sectors (columns 3 and 4). As shown, the point estimate for β_1, our coefficient of interest, are similar in magnitude to those reported in Table A2. The results indicate that potential differences between state-owned and private firms operating in the same sector and province due to differential demand from the construction and utilities sector are not driving our results.

7 Conclusions

This paper studies credit allocation across firms in a dynamic economy with financial frictions. Adding to the existing literature, we show that recessions can hinder efficient factor reallocation. This is the result of two forces: (i) financial frictions favoring state-connected firms becoming more prominent during recessions – for example, due to implicit bail-out of SOEs or career concerns of loan officers –, and (ii) lower average productivity of state-connected firms. Policy-driven credit expansions in response to recessions can amplify this effect.

Our empirical analysis focuses on the Chinese economic stimulus plan introduced at the end of 2008 in response to the Great Recession. In particular, we focus on the credit expansion policies such as lower required reserve ratios and lower benchmark lending rates for commercial banks. We show that these credit expansion policies had a broader impact on the Chinese economy besides facilitating off-balance-sheet borrowing by local governments, an aspect so far overlooked by the existing literature. To this end we matched confidential loan level data from the 19 largest Chinese banks with firm-level data from Annual Survey of Industrial Firms. WE exploit the loan level nature of the data to construct plausibly exogenous changes in bank credit supply at firm-level. We show that – during the stimulus years – new credit was allocated relatively more towards state-owned or state-controlled firms and firms with lower initial marginal productivity of capital, corroborating our theoretical mechanism.

Our findings illustrate how financial frictions, business cycle, and credit expansion can interact, leading to potentially unintended consequences of intervention policy. They are therefore 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

Acharya, V. V., T. Eisert, C. Eufinger, and C. W. Hirsch (2017). Whatever it takes: The real effects of unconventional monetary policy.

Archarya, V., J. Qian, and Z. Yang (2016). In the shadow of banks: Wealth management products and bank risk.

Bai, C.-E., C.-T. Hsieh, and Z. M. Song (2016). The long shadow of a fiscal expansion.

Barlevy, G. (2003). Credit market frictions and the allocation of resources over the business cycle. *Journal of monetary Economics 50*(8), 1795–1818.

Bartik, T. (1991). Who benefits from state and local economic development policies?

Bernanke, B. and M. Gertler (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review*, 14–31.

Blanchard, O. J., L. F. Katz, R. E. Hall, and B. Eichengreen (1992). Regional evolutions. *Brookings papers on economic activity 1992*(1), 1–75.

Bleck, A. and X. Liu (2014). Credit expansion and credit misallocation. *Available at SSRN 1945701*.

Boyreau-Debray, G. and S.-J. Wei (2005). Pitfalls of a state-dominated financial system: The case of china. Technical report, national bureau of Economic research.

Brandt, L., C. Hsieh, and X. Zhu (2005). China's structural transformation. *Mimeographed, University of California, Berkeley*.

Brandt, L. and X. Zhu (2000). Redistribution in a decentralized economy: growth and inflation in china under reform. *Journal of Political Economy 108*(2), 422–439.

Brunnermeier, M., M. Sockin, and W. Xiong (2017). China's gradualistic economic approach: Does it work for financial development? *Forthcoming in American Economic Review Papers & Proceedings*.

Brunnermeier, M. K., M. Sockin, and W. Xiong (2016). China's model of managing the financial system. Technical report, Working paper, Princeton University.

Buera, F. J. and Y. Shin (2013). Financial frictions and the persistence of history: A quantitative exploration. *Journal of Political Economy 121*(2), 221–272.

Caballero, R. J., M. L. Hammour, et al. (1994). The cleansing effect of recessions. *American Economic Review 84*(5), 1350–68.

Chakraborty, I., I. Goldstein, and A. MacKinlay (2016). Housing price booms and crowding-out effects in bank lending.

Chang, C., Z. Liu, M. M. Spiegel, J. Zhang, et al. (2017). Reserve requirements and optimal chinese stabilization policy. Technical report.

Chen, Z., Z. He, and C. Liu (2017). The financing of local government in china: Stimulus loan wanes and shadow banking waxes. *Working Paper*.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Cooper, R., J. Haltiwanger, et al. (1993). The aggregate implications of machine replacement: Theory and evidence. *American Economic Review 83*(3), 360–82.

Deng, Y., R. Morck, J. Wu, and B. Yeung (2015). China's pseudo-monetary policy. *Review of Finance 19*(1), 55–93.

Firth, M., C. Lin, P. Liu, and S. M. Wong (2009). Inside the black box: Bank credit allocation in china's private sector. *Journal of Banking & Finance 33*(6), 1144–1155.

Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez (2015). "Capital Allocation and Productivity in South Europe".

Greenstone, M., A. Mas, and H.-L. Nguyen (2015). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and normal economic times.

Hachem, K. C. and Z. M. Song (2016). Liquidity regulation and unintended financial transformation in china.

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

Hsieh, C.-T. and Z. M. Song (2015). "Grasp the Large, Let Go of the Small: the Transformation of the State Sector in China".

Huang, Y., M. Pagano, and U. Panizza (2016). Public debt and private firm funding: Evidence from chinese cities.

Kashyap, A. K. and J. C. Stein (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 407–428.

Khwaja, A. I. and A. Mian (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *The American Economic Review 98*(4), 1413–1442.

King, R. G. and R. Levine (1993). Finance and growth: Schumpeter might be right. *The quarterly journal of economics*, 717–737.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *Journal of political economy 105*(2), 211–248.

Kornai, J., E. Maskin, and G. Roland (2003). Understanding the soft budget constraint. *Journal of economic literature 41*(4), 1095–1136.

Mortensen, D. T. and C. A. Pissarides (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies 61*(3), 397–415.

Ouyang, M. and Y. Peng (2015). The treatment-effect estimation: A case study of the 2008 economic stimulus package of china. *Journal of Econometrics 188*(2), 545–557.

Ramey, G. and J. Watson (1997). Contractual fragility, job destruction, and business cycles. *The Quarterly Journal of Economics 112*(3), 873–911.

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics 11*(4), 707–720.

Shleifer, A. and R. W. Vishny (1994). Politicians and firms. *The Quarterly Journal of Economics 109*(4), 995–1025.

Shleifer, A. and R. W. Vishny (2010). Asset fire sales and credit easing. *The American Economic Review 100*(2), 46–50.

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

Stein, J. C. (1998). An adverse-selection model of bank asset and liability management with implications for the transmission of monetary policy. *RAND Journal of Economics 29*(3), 466–486.

Steinfeld, E. S. (2000). *Forging reform in China: The fate of state-owned industry.* Cambridge University Press.

Wang, H., H. Wang, L. Wang, and H. Zhou (2016). Shadow banking: China's dual-track interest rate liberalization.

Wen, Y. and J. Wu (2014). Withstanding great recession like china. *FRB of St. Louis Working Paper No*.

Figures and Tables

Figure 1: Structure of China Economic Stimulus Plan

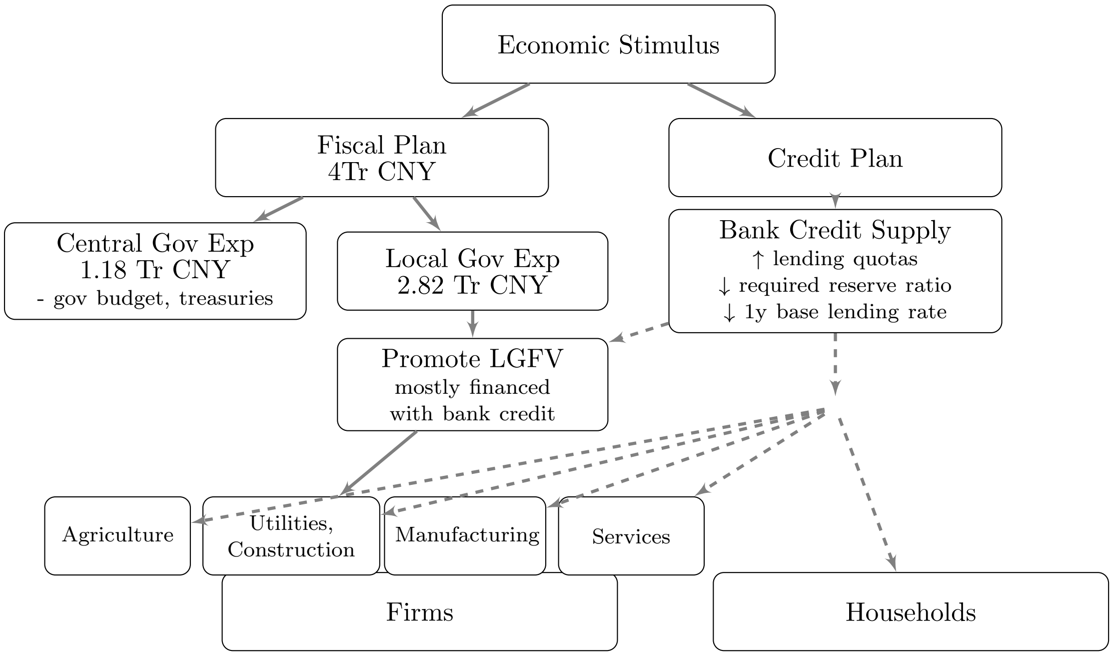
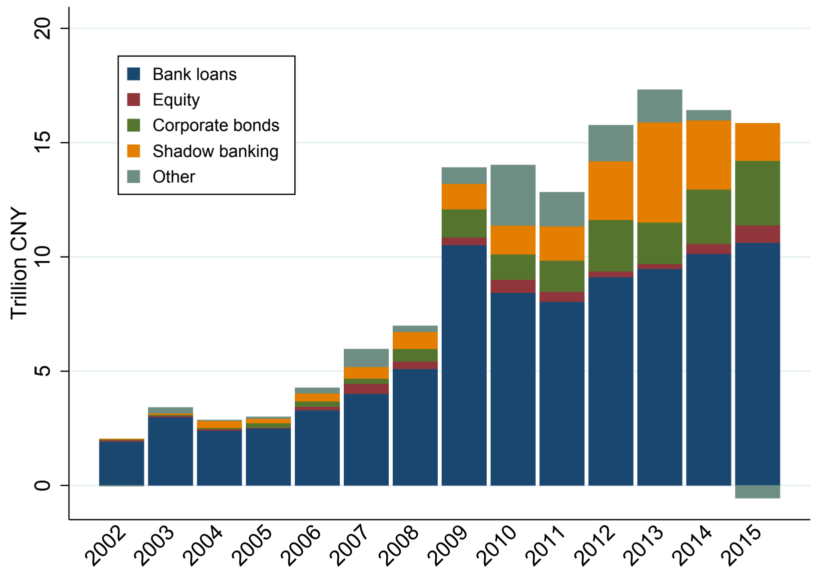


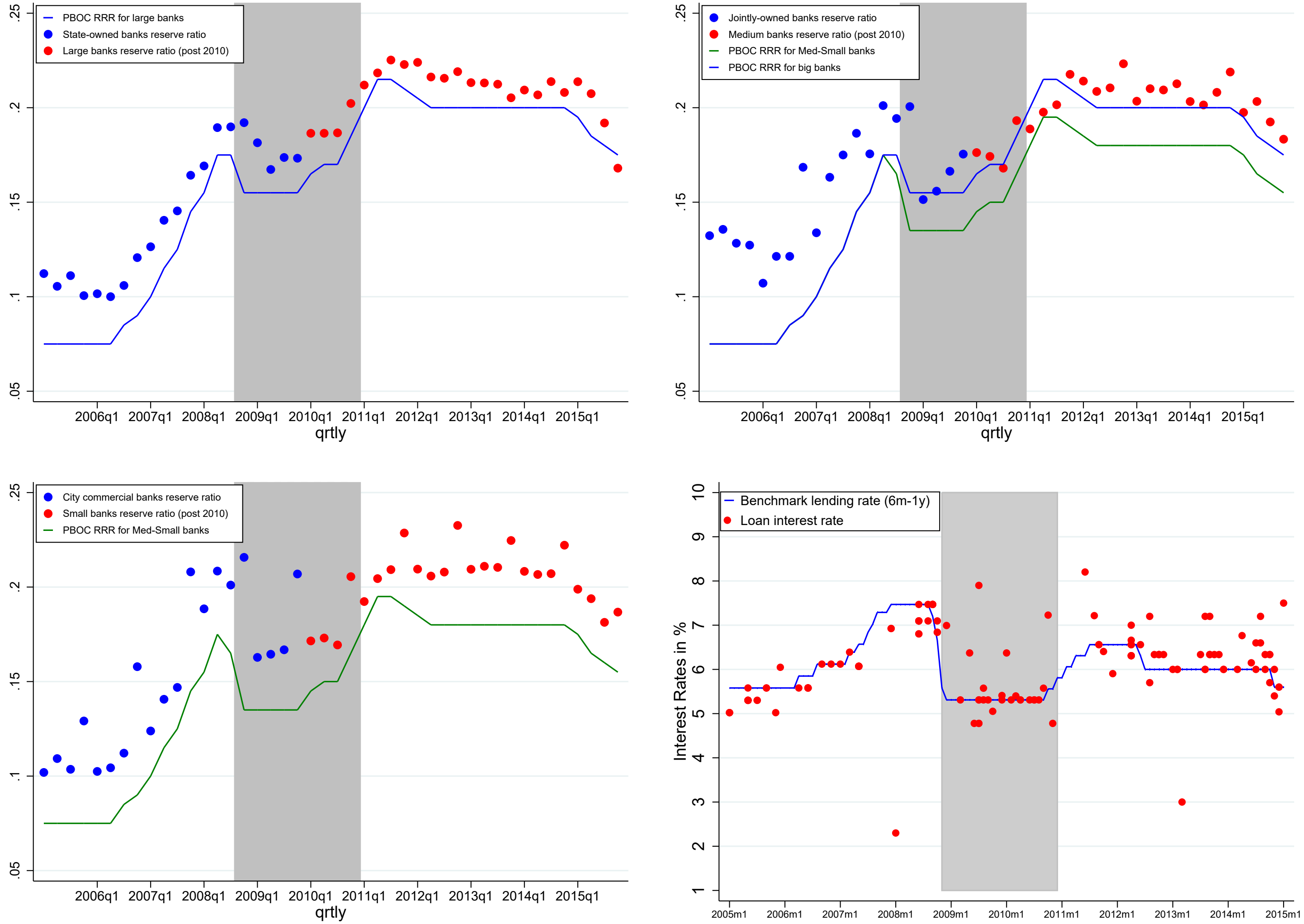
Figure 2: Aggregate Financing to the Real Economy (Flow, AFRE-F)



Notes: Source: Total Social Financing Dataset (TSF) of the People Bank of China. The category "shadow banking" includes loans by trust companies (trust loans) and entrusted firm-to-firm loans (entrusted loans). The category "other" includes bankers' acceptances and credit operations categorized under "other" in the TSF data.

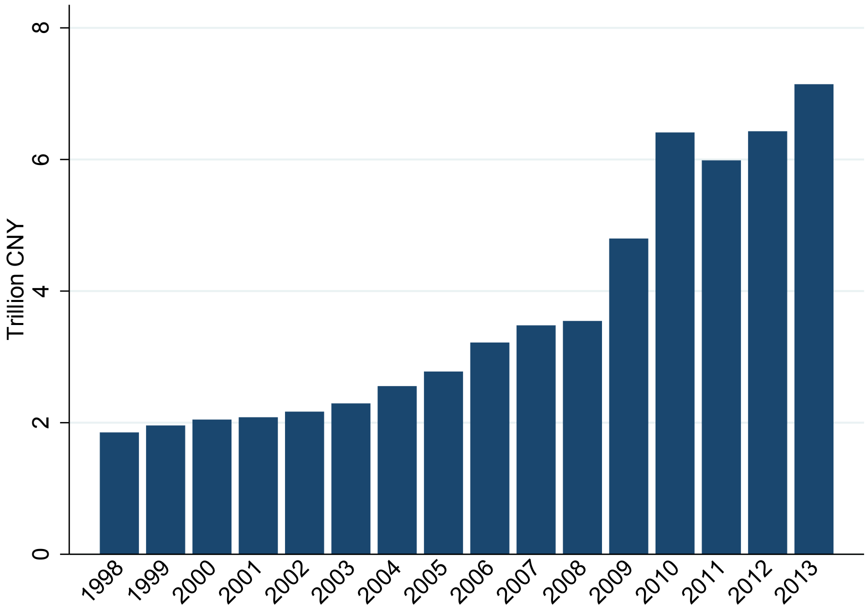
Figure 3: Changes in Banking Regulation during Stimulus Years:

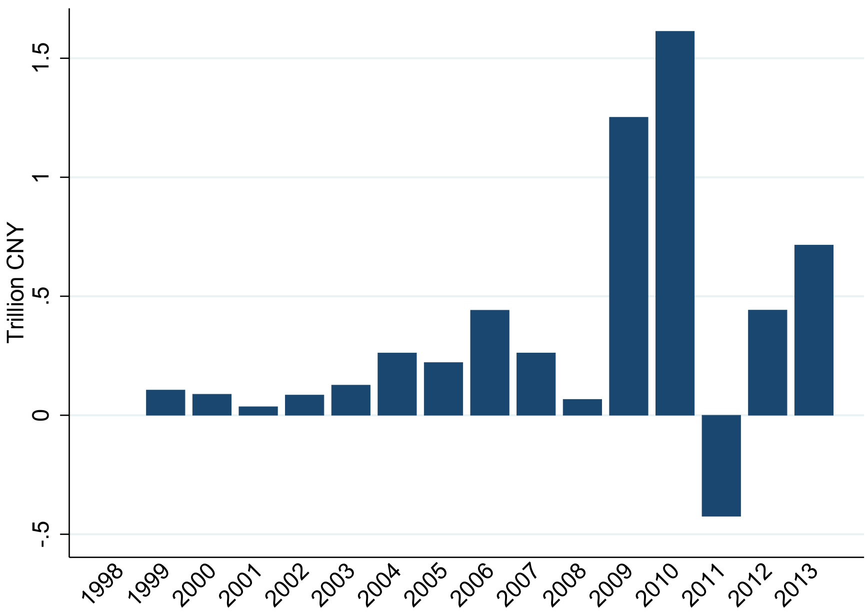
Bank Required Reserve Ratio (RRR) and Benchmark Lending Rate



Notes: Shaded areas indicate stimulus program period (2008:Q4 to 2010:Q4). Data on actual reserve ratios is from WIND and comes aggregated by bank category. Banks are categorized by WIND into: state-owned, jointly-owned, and city commercial banks before 2010. Starting from 2010, these three categories have been re-labeled as, respectively: large, medium, and small banks, which is why we report them in different colors in the graphs. We match the WIND categories to the Central Bank categories of "large" and "medium and small" banks to which different RRR apply. For the joint-owned (then medium) banks, we report both RRRs as some of them are subject to the RRR for large banks. In the bottom-right graph we report the benchmark lending rate set by the Central Bank for loans with maturity between 6 months and 1 year. As a sanity check, we report in the same graph the interest rate of loans to Chinese publicly listed firms as officially announced in company statements.

Figure 4: Long-term Liabilities: Level and Change

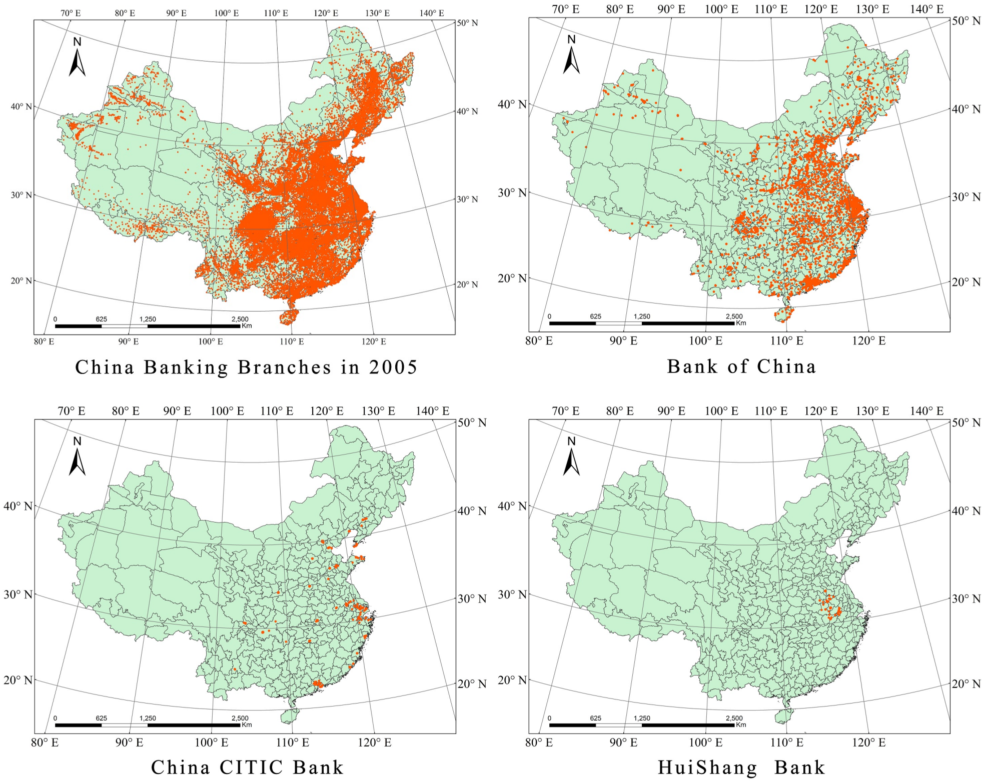




Notes: Source: National Bureau of Statistics, Annual Industrial Survey. The upper graph reports the sum across firms of the monetary value of long-term liabilities in each year. The lower graph reports the year on year difference of this sum. To insure comparability over time, we focus exclusively on manufacturing firms with annual revenues above 20 million CNY (CPI adjusted, in 2000 CNY), for which the survey is effectively a Census between 1998 and 2013.

Figure 5: Geographical Location of Bank Branch Networks

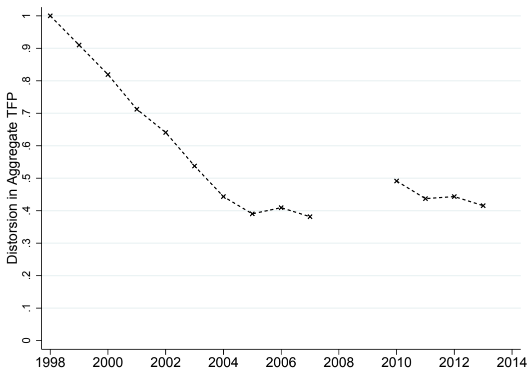
Mainland China, Hong Kong and Macao



Notes: Source: China Banking Regulatory Commission. Branch location refers to year 2005.

Figure 6: Measure of Misallocation

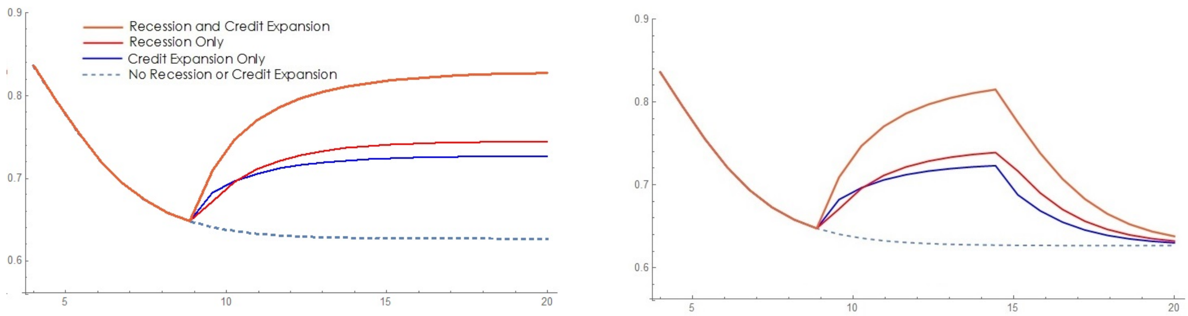
Chinese Industrial Sector - 1998 to 2013



Notes: The measure of distortion is computed as described in equation (5) assuming capital share $\alpha = 0.5$. The measure d_t is normalized so that its 1998 level is equal to 1. To construct the measure of distortion we use the definition of SOE described in Section 4. As shown in Table 1, this variable is not available in 2008 and 2009.

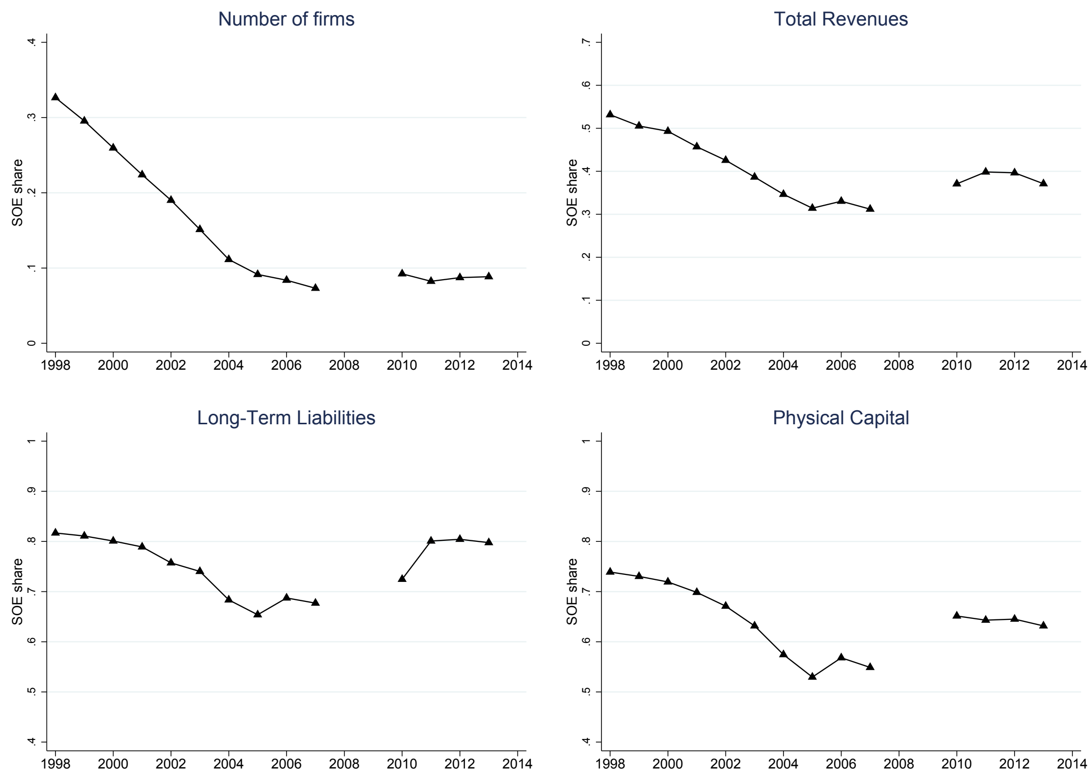
Figure 7: Dynamics of Resource Allocation:
Shares of Bank Credit to S Firms

(a) Permanent Credit Expansion and Recession (b) Temporary Credit Expansion and Recession



Notes: Based on simulation using $\chi = 1.57$ (Song et al. (2011)), $\eta = 0.36$ (WB Doing Business), $A = 1$, $\theta = 1.5$, $\alpha = 0.35$, $\phi = 0.5$, $\beta = 0.95$, $N = M = 1$. Panel (a) illustrates the scenario in which recession and credit expansion occur at T=8 and are permanent, whereas (b) illustrates the scenario where recession and credit expansion occur at T=8 but, after 6 periods, the economy recovers and the government reduces the credit supply to the original level. In our baseline before recession or credit expansion we set: $Q = 0.38$ and $\mu = 0.91$. The four lines from top to bottom represent an economy (1) with credit expansion in recession ($Q = 0.43$ and $\mu = 0.89$), (2) with recession only ($Q = 0.38$ and $\mu = 0.89$), (3) with credit expansion only ($Q = 0.43$ and $\mu = 0.91$), (4) without recession and credit expansion ($Q = 0.38$ and $\mu = 0.91$).

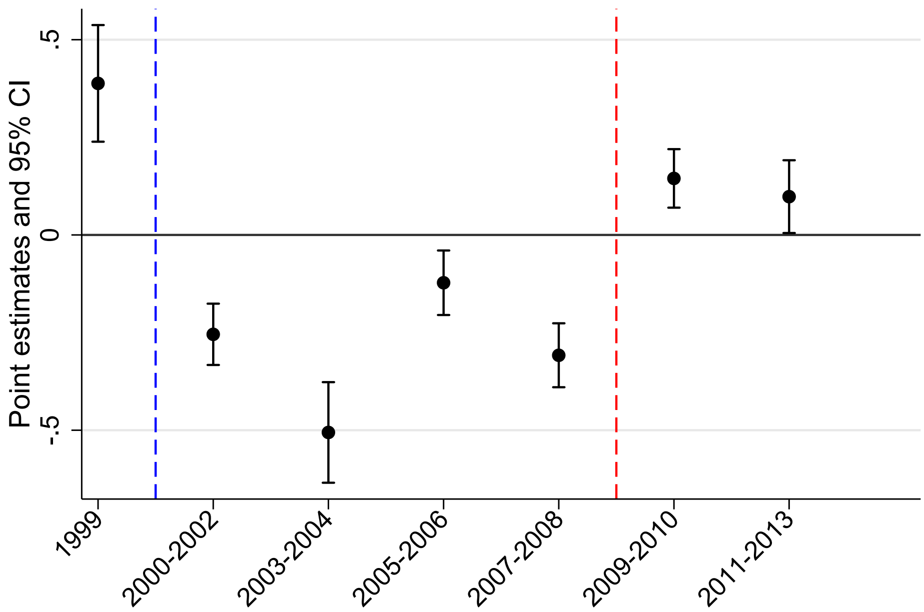
Figure 8: Share of State Owned Firms
Chinese Industrial Sector - 1998 to 2013



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 as described in Section 4. As shown in Table 1, this variable is not available in 2008 and 2009.

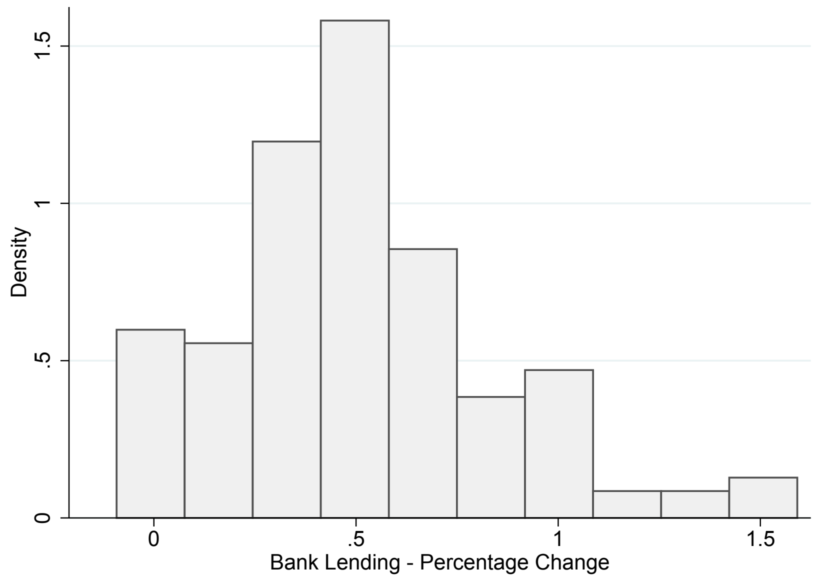
Figure 9: State-Ownership and New Loans Over Time

Estimated Coefficients and 95 percent Confidence Intervals



Notes: The figure shows the estimated coefficient β in equation (1) when $C_{icjt-1} = I(\text{State Owned Firm})_{icjt-1}$, 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 10: Change in Bank Lending under Economic Stimulus



Notes: The histogram reports the percentage change in inflation adjusted bank lending between 2007-2008 (pre-stimulus years) and 2009-2010 (stimulus years). For each bank, we compute it as $\Delta\text{Bank Lending} = (\frac{1}{2}\sum_{t=09}^{T=10}\text{Loans}_{bt} - \frac{1}{2}\sum_{t=07}^{T=08}\text{Loans}_{bt})/\frac{1}{2}\sum_{t=07}^{T=08}\text{Loans}_{bt}$. Source: Bankscope, variable code for Loans_{bt} is $BANK2000$.

Table 1: Summary Statistics

Annual Survey of Industrial Firms, 1998-2013

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

Basic Correlations in the Data

Dep. var. : $\frac{\Delta LTLiab_t}{Rev_{t-1}}$	old SOE policy	new SOE policy				stimulus	post-stimulus
	1999	2000-2002	2003-2004	2005-2006	2007-2008	2009-2010	2011-2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
I(State Owned Firm)	0.364***	-0.264***	-0.480***	-0.125***	-0.304***	0.155***	0.098**
	[0.077]	[0.040]	[0.066]	[0.042]	[0.042]	[0.039]	[0.048]
Observations	38,122	143,003	71,469	229,283	273,640	209,217	292,581
R-squared	0.050	0.021	0.028	0.011	0.016	0.017	0.035
Panel B							
$\log MPK$	0.022	0.161***	0.197***	0.096***	0.125***	-0.065***	
	[0.024]	[0.011]	[0.016]	[0.010]	[0.007]	[0.006]	
Observations	38,122	143,003	71,469	124,875	273,640	209,217	
R-squared	0.049	0.022	0.029	0.021	0.017	0.018	
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

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 Owned Firm) is an indicator function that takes value 1 if a firm is defined as State-Owned-Enterprise according to definition in section 4. Firm ownership status is defined in year $t-1$, with the only exception of years 2009 and 2010, where firm ownership status refers to 2007. This is because, as shown in Table 1, this variable is not available in the years 2008 and 2009. $\log MPK$ is the natural log of industrial value added divided by book value of fixed assets. It is defined in year $t-1$, with the only exception of years 2009 and 2010, where $\log MPK$ refers to year 2007. Notice also that information on industrial value added is not available in our data for the years 2011 to 2013, which is why the estimated coefficient is missing in column (7). All regression include as control for firm size the 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, in 2000 CNY). Standard errors are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Bank Credit Supply and Loans

outcome:	Δ log loan balance$_{ibt}$									
sample:	All years 2006-2013					Stimulus years: 2009-2010				
	all firms	all firms	multi-lender	multi-lender	multi-lender	all firms	all firms	multi-lender	multi-lender	multi-lender
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta \log L_{b-i,t}$	0.184	0.173	0.185	0.171	0.193	0.134	0.109	0.148	0.122	0.139
	[0.014]***	[0.014]***	[0.016]***	[0.016]***	[0.018]***	[0.024]***	[0.024]***	[0.027]***	[0.027]***	[0.031]***
borrower characteristics:		y		y			y		y	
fixed effects:										
year	y	y	y	y	y	y	y	y	y	y
province		y		y	y		y		y	y
industry		y		y	y		y		y	y
firm $\times$ year					y					y
R-squared	0.003	0.008	0.008	0.008	0.348	0.002	0.011	0.002	0.013	0.355
Observations	194,266	194,266	150,032	150,032	150,443	41,953	41,953	32,245	32,197	32,245

Notes: The unit of observation is a bank-firm credit relationship. The dependent variable is yearly change in the log of the outstanding loan balance lent from bank b to firm i. Borrower characteristics include: firm size in terms of number of workers (in logs), export status (dummy equal to 1 if a firm has positive value of export in a given year), and firm age. Borrowers controls are observed in year $t-1$. Standard errors are clustered at the borrower level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The Effect of Bank Credit Supply on Firm Borrowing
Stimulus Years (2009-2010)

outcome:	Δ log loan balance $_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widetilde{L_{it}}$	0.800	0.743	0.740	0.703	0.705	0.705
	[0.075]***	[0.076]***	[0.076]***	[0.078]***	[0.077]***	[0.077]***
$\Delta\widetilde{L_{it}} \times I(SOE)_{i,t=0}$			0.121	0.126		
			[0.070]*	[0.069]*		
$\Delta\widetilde{L_{it}} \times \log APK_{i,t=0}$					-0.071	-0.064
					[0.027]***	[0.027]**
$I(SOE)_{i,t=0}$			-0.068	-0.023		
			[0.013]***	[0.015]		
$\log APK_{i,t=0}$				0.031	0.050	0.041
				[0.004]***	[0.005]***	[0.006]***
firm controls		y		y		y
fixed effects:						
year	y	y	y	y	y	y
province		y		y		y
industry		y		y		y
R-squared	0.029	0.057	0.031	0.063	0.043	0.063
Observations	10,298	10,298	10,438	10,287	10,287	10,287

Notes: The unit of observation is a firm. The dependent variable is the yearly change in the log of the total outstanding loan balance of firm i. The variable I(State Owned Firm) is an indicator function equal to 1 if the firm is a SOE, and it is defined in 2007. We define SOE as described in Section 4. $\log APK$ is the logarithm of industrial value added divided by book value of fixed assets, and it is defined in 2007. Borrower characteristics include: firm size in terms of number of workers (in logs), export status (dummy equal to 1 if a firm has positive value of export in a given year), and firm age. Borrowers controls are observed in year $t-1$. Standard errors are clustered at the borrower level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The Effect of Bank Credit Supply on Firm Borrowing
Pre-Stimulus Years, Stimulus Years, Post-Stimulus Years

outcome	Δ log loan balance$_{it}$					
time period	pre-stimulus (2007-2008)		stimulus (2009-2010)		post-stimulus (2010-2013)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widetilde{L_{it}}$	0.738	0.708	0.703	0.705	1.659	1.663
	[0.102]***	[0.101]***	[0.078]***	[0.077]***	[0.066]***	[0.066]***
$\Delta\widetilde{L_{it}} \times I(SOE)_{i,t=0}$	-0.214		0.126		-0.072	
	[0.074]***		[0.069]*		[0.047]	
$\Delta\widetilde{L_{it}} \times \log APK_{i,t=0}$		0.056		-0.064		0.079
		[0.027]**		[0.027]**		[0.017]***
$I(SOE)_{i,t=0}$	0.022		-0.023		-0.008	
	[0.013]*		[0.015]		[0.012]	
$\log APK_{i,t=0}$	0.030	0.024	0.031	0.041	0.025	0.011
	[0.004]***	[0.005]***	[0.004]***	[0.006]***	[0.003]***	[0.004]***
firm controls	y	y	y	y	y	y
fixed effects:						
year	y	y	y	y	y	y
province	y	y	y	y	y	y
industry	y	y	y	y	y	y
R-squared	0.059	0.059	0.063	0.063	0.088	0.088
Observations	12,628	12,628	10,287	10,287	22,906	22,906

Notes: The unit of observation is a firm. The dependent variable is the yearly change in the log of the total outstanding loan balance of firm i. The variable I(State Owned Firm) is an indicator function equal to 1 if the firm is a SOE. It is defined in 2006 for years 2006 to 2008, in 2007 for years 2009 and 2010, in 2010 for years 2011 to 2013. We define SOE as described in Section 4. Borrower characteristics include: firm size in terms of number of workers (in logs), export status (dummy equal to 1 if a firm has positive value of export in a given year), and firm age. Borrowers controls are observed in year $t-1$. Standard errors are clustered at the borrower level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The Effect of Bank Credit Supply on Investment and Employment
All firms, SOEs and Private Firms. All Years and Stimulus Years

outcome:	$\frac{\Delta K_{it}}{Assets_{it-1}}$					Δ log Employment$_{it}$				
	all years	all years		stimulus		all years	all years		stimulus	
sample:	all firms	SOEs	Private	SOEs	Private	all firms	SOEs	Private	SOEs	Private
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\widetilde{L_{it}}$	0.107	-0.055	0.154	0.183	0.020	0.092	0.198	0.089	0.014	0.006
	[0.046]**	[0.107]	[0.051]***	[0.109]*	[0.045]	[0.053]*	[0.121]	[0.058]	[0.133]	[0.079]
firm controls	y	y	y	y	y	y	y	y	y	y
fixed effects:										
year	y	y	y	y	y	y	y	y	y	y
province	y	y	y	y	y	y	y	y	y	y
industry	y	y	y	y	y	y	y	y	y	y
R-squared	0.165	0.118	0.187	0.227	0.120	0.038	0.056	0.038	0.247	0.180
Observations	45,846	10,970	34,876	2,641	7,657	45,846	10,970	34,876	2,641	7,657

Notes: The unit of observation is a firm. The dependent variables are: the yearly change in total fixed assets divided by total assets in year $t-1$ (columns 1 to 5); the yearly change in the log of average number of workers (columns 6 to 10). Borrower characteristics include: firm size in terms of number of workers (in logs), export status (dummy equal to 1 if a firm has positive value of export in a given year), and firm age. Borrowers controls are observed in year $t-1$. Standard errors are clustered at the borrower level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Appendix 1: City-Level Exposure: Discussion of Identification Assumptions

Define $Loans_{bt}$ as the national level of corporate lending of bank b at time t. Let us rewrite the national lending of a given bank as a function of supply and demand shifters:

$$\Delta Loans_{bt} = D_t^{\omega} Q_{bt}^{\kappa} = (\Pi_p(\Pi_c D_{ct}^{\mu_c})^{\mu_p} \Pi_j D_{jt}^{\nu_j})^{\omega} Q_{bt}^{\kappa} \tag{17}$$

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-specific characteristics such as the bank's overall financial health or its cost of funds. Notice that equation (17) implicitly assumes that all banks face the same national demand schedule.[52]

It is useful to plug this simple definition of bank lending at national level into equation (10) to obtain:

$$\widetilde{l_{ct}} = \sum_b \omega_{bc,t=0} (\Pi_p(\Pi_c D_{ct}^{\mu_c})^{\mu_p} \Pi_j D_{jt}^{\nu_j})^{\omega} Q_{bt}^{\kappa} \tag{18}$$

Equation (18) shows that local shocks to demand in city c and province p where firm i operates enter into the definition of $\widetilde{l_{ct}}$, violating the identification assumption. Similarly, national shocks to demand in sector j where firm i operates also enter into the definition of $\widetilde{l_{ct}}$. One potential solution often used in the construction of Bartik-style shocks is to remove lending to the specific *location* or *sector* where firm i operates from the summation in equation (18). In our setting, we cannot pursue this route, 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 (18) as follows:

$$\widetilde{l_{ct}} = (\Pi_p(\Pi_c D_{ct}^{\mu_c})^{\mu_p} \Pi_j D_{jt}^{\nu_j})^{\omega} \sum_b \omega_{bc,t=0} Q_{bt}^{\kappa}$$

Taking logs on both sides we obtain:

$$\log \widetilde{l_{ct}} = \omega\mu_p \log(\Pi_p(\Pi_c D_{ct}^{\mu_c})) + \omega\nu_j \log(\Pi_j D_{jt}) + \log \sum_b \omega_{bc,t=0} Q_{bt}^{\kappa} \tag{19}$$

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

[52] 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.

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 fixed effects, as follows:

$$\log l_{icjt} \quad = \quad \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta \log \widetilde{l_{ct}} + \varepsilon_{icjt} \tag{20}$$

Equation (20) is the equation that we estimate in the data. To show that the coefficient β on $\log \widetilde{l_{ct}}$ captures exclusively changes in credit supply, let us substitute in equation (20) the definition of $\log \widetilde{l_{ct}}$ obtained in equation (19):

$$\begin{aligned} \log l_{icjt} \quad &= \quad \alpha_t + \alpha_{pt} + \alpha_{jt} + \beta\omega\mu_p \log(\Pi_p(\Pi_c D_{ct}^{\mu_c})) + \beta\omega\nu_j \log(\Pi_j D_{jt}) \\ &+ \quad \beta \log \sum_b \omega_{bc,t=0} Q_{bt}^{\kappa} + \varepsilon_{icjt} \end{aligned} \tag{21}$$

Notice from equation (21) that fixed effects at sector level interacted with time dummies (α_{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 strong assumption that credit demand shifters are highly correlated across cities within the same province. We partially relax this assumption in the empirical analysis by controlling for initial city characteristics interacted with year fixed effects. To the extent that differences in business cycle across cities within the same province are determined by differences in initial city characteristics, such as income per capita, size, or share of rural population, then these controls fully capture city-level demand shifters.

Under this assumption, equation (21) can be rewritten as:

$$\log l_{icjt} \quad = \quad \delta_t + \delta_{pt} + \delta_{jt} + \beta \log \sum_b \omega_{bc,t=0} Q_{bt}^{\kappa} + \varepsilon_{icjt} \tag{22}$$

where: $\delta_t = \alpha_t$; $\delta_{pt} = \alpha_{pt} + \beta\omega\mu_p \log(\Pi_p(\Pi_c D_{ct}^{\mu_c}))$; $\delta_{jt} = \alpha_{jt} + \beta\omega\nu_j \log(\Pi_j D_{jt})$

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 β should capture variation in firm-level borrowing that is exclusively driven by bank level credit supply shocks. In other words, when estimating equation (20) 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.

Appendix 2: Additional Tables

Table A1: Balancedness Test

	Exposure to credit supply shock below	above	diff	p-value
City characteristics:				
log gdp per capita	0.152	0.255	0.103	0.086
share of rural population	0.651	0.669	0.018	0.241
log population density	5.763	5.603	-0.160	0.038
log population	5.943	5.677	-0.267	0.000

Notes: The table reports average 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. City characteristics observed in 2005, N = 557.

Table A2: The Effect of Bank Credit Supply on Firm Borrowing: Heterogeneous Effects

Additional Specification using City-Level Exposure - Stimulus years 2009 and 2010

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
Exposure to Credit Supply Shock	0.249***	0.210**	0.167**	0.127	0.466***	0.437***
	[0.086]	[0.088]	[0.082]	[0.085]	[0.130]	[0.133]
Exposure to Credit Supply Shock $\times I$(State Owned Firm)			1.322**	1.288**		
			[0.586]	[0.586]		
Exposure to Credit Supply Shock $\times \log MPK$					-0.320***	-0.333***
					[0.092]	[0.093]
I(State Owned Firm)			-16.581**	-16.066**		
			[7.417]	[7.415]		
$\log MPK$					3.950***	4.096***
					[1.167]	[1.173]
size (log L)		-0.121***		-0.129***		-0.148***
		[0.021]		[0.020]		[0.021]
export status		-0.072		-0.070		-0.092**
		[0.045]		[0.045]		[0.045]
age (years)		0.003		0.002		0.003
		[0.003]		[0.003]		[0.003]
year fe	y	y	y	y	y	y
2-digit province $\times$ year fe	y	y	y	y	y	y
4-digit industry $\times$ year fe	y	y	y	y	y	y
city initial characteristics $\times$ year fe		y		y		y
Observations	191,234	191,234	191,234	191,234	191,234	191,234
R-squared	0.024	0.024	0.024	0.024	0.024	0.024

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, and it is defined in 2007. We define SOE as described in Section 4. $\log MPK$ 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 A3: The Effect of Bank Credit Supply on Firm Borrowing: Heterogeneous Effects

Additional Specification using City-Level Exposure - Stimulus years 2009 and 2010

Robustness to Excluding Input Suppliers to Construction and Utilities

	(1)	(2)	(3)	(4)
VARIABLES	Excluding Basic Metals Production		Excluding Mining and Quarrying	
Exposure to Credit Supply Shock	0.100	0.411***	0.178**	0.456***
	[0.086]	[0.134]	[0.087]	[0.134]
Exposure to Credit Supply Shock $\times I$(State Owned Firm)	1.296**		1.155*	
	[0.597]		[0.606]	
Exposure to Credit Supply Shock $\times \log MPK$		-0.336***		-0.307***
		[0.094]		[0.095]
I(State Owned Firm)	-16.174**		-14.390*	
	[7.550]		[7.672]	
$\log MPK$		4.130***		3.766***
		[1.193]		[1.197]
size (log L)	-0.122***	-0.143***	-0.114***	-0.133***
	[0.021]	[0.021]	[0.021]	[0.021]
export status	-0.057	-0.080*	-0.070	-0.091**
	[0.045]	[0.045]	[0.045]	[0.045]
age (years)	0.001	0.002	0.003	0.004
	[0.003]	[0.003]	[0.003]	[0.003]
year fe	y	y	y	y
2-digit province $\times$ year fe	y	y	y	y
4-digit industry $\times$ year fe	y	y	y	y
city initial characteristics $\times$ year fe	y	y	y	y
Observations	184,695	184,695	182,562	182,562
R-squared	0.024	0.024	0.024	0.024

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, and it is defined in 2007. We define SOE as described in Section 4. $\log MPK$ 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. Basic Metals production include: smelting and pressing of ferrous metals (iron and steel) and non-ferrous metals. Mining and quarrying includes: coal mining and dressing, petroleum and natural gas extraction, mining and dressing of ferrous and non-ferrous metals, non-metal ores and other mining industries. Standard errors are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.