Credit Allocation under Economic Stimulus: Evidence from China*

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Abstract

We study credit allocation across firms and its real effects during China's economic stimulus plan of 2009-2010. We match confidential loan-level data from the 19 largest Chinese banks with firm-level data on manufacturing firms. We document that the stimulus-driven credit expansion disproportionately favored state-owned firms and firms with lower average product of capital, reversing the process of capital reallocation towards private firms that characterized China high growth before 2008. We argue that implicit government guarantees favoring state-owned firms become more prominent during recessions and can explain this reversal.

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1 Introduction

In response to the global financial crisis, governments around the world introduced large economic stimulus programs. Several studies have analyzed the effect of government interventions on economic activity in the United States during the Great Recession. In the same years, governments in emerging economies also introduced stimulus programs – in some cases larger than the US as a share of their GDP. However, there is scarce empirical evidence on the effects of these programs in emerging economies, and on their potential unintended consequences in terms of allocation of capital and labor across firms. This is an important concern, especially in countries with less developed financial markets.[1]

In this paper we use micro data to study the allocation of bank credit across firms in China, and how it has changed following the introduction of a major credit expansion program. At the end of 2008, the Chinese government introduced an economic stimulus plan to mitigate the effects of the global financial crisis. The plan had two main components. First, an increase in government spending of 4 Trillion RMB – or 12.6% of China GDP in 2008 – over two years, mostly on infrastructure projects and social welfare policies.[2] Local governments in large part financed this increase in spending through so-called "local government financing vehicles" (LGFVs), off-balance-sheet companies set up to increase local government expenditure without officially running a deficit. The second component of the stimulus plan entailed a set of credit expansion policies – including lower bank reserve requirements and lower benchmark lending rates – aimed at increasing lending to the real economy by Chinese banks. As shown in Figure 1, following the introduction of these credit expansion policies, new bank loans by Chinese banks doubled with respect to their 2008 level.

The objective of this paper is twofold. First, to provide micro-evidence on the impact of the Chinese credit stimulus plan on firm borrowing and real outcomes. Second, and more importantly, to provide new evidence on how capital allocation across firms has evolved in China during the last two decades. In particular, we compare capital allocation across firms in the period before the stimulus plan – characterized by fast economic growth and increase in market share of private firms – with the period after the stimulus plan. Our evidence is based on confidential loan-level data collected by the China Banking Regulatory Commission covering the 19 largest Chinese banks and 80% of bank lending to firms in China, including both private and publicly-listed firms. Using unique firm identifiers we match loan-level with firm-level data from the Chinese Annual Industrial Survey. The merged dataset contains information on both banking relationships and firm real outcomes such as investment and employment, as well as firm ownership information.

[1] Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015).

[2] 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 in 2008.

This allows us to study credit allocation across firms with different initial characteristics – such as productivity and state-ownership. A key innovation of this paper is therefore to provide a detailed view of both borrowing activity and real effects for a large set of firms in China and a time period encompassing both the years before and after the introduction of the stimulus plan.

The main identification challenge we face is to isolate changes in firm borrowing that are solely driven by credit supply forces instead of credit demand or investment opportunities. To this end, we use loan-level data to construct a measure of firm exposure to credit supply generated by the stimulus plan. Our methodology exploits two sources of variation: first, Chinese banks increased their aggregate lending differently in response to the stimulus policies; second, Chinese firms had different pre-existing relationships with different banks. Similar to the methodology used by Chodorow-Reich (2014) with US data, we define our measure of exposure to credit supply for a given firm as the average change in aggregate lending by a firm's pre-existing lenders. To remove region-specific and industry-specific credit demand shocks, we build our firm-level measure of exposure using only aggregate lending to firms that operate in different cities and sectors. We validate this strategy in two ways. First, we show that lending relationships are extremely persistent in China. In our data, 95% of new loans are originated by banks with which a firm had a pre-existing credit relationship. Second, following Khwaja and Mian (2008), we show that our measure of exposure explains firm borrowing from a given bank even when fully controlling for firm fixed effects interacted with year fixed effects, which absorb any firm-specific variation in demand or investment opportunities.

We first focus on the stimulus years 2009 and 2010 and study the average effect of a credit-supply increase under China's stimulus plan on firm borrowing, investment and employment. We document that our measure of credit-supply increase explains variation in firm borrowing, and that higher bank credit had positive and significant effects on investment and employment. Our estimated elasticities indicate that, during the stimulus years, firms with a 1 percent larger increase in credit experienced a 0.1 percentage points larger increase in investment as a share of value of production, and a 0.3 percent larger increase in number of workers. While a large literature has documented the financial and real effects of credit supply changes in different settings and with similar identification strategies, the contribution of this first part of the paper is to provide such estimates for China.[3]

Next, we study how credit allocation across firms has evolved in China over time. For this purpose, we apply our identification strategy to all years available in the micro-data sample, which include both the pre-stimulus and the post-stimulus periods. In particular, we are interested in studying the role played by firm productivity on the dynamics of

[3]See, for : Peek and Rosengren (2000), Chaney, Sraer, and Thesmar (2012), Jiménez, Ongena, Peydró, and Saurina (2014).

credit allocation.

Our results indicate a change in the trend of capital allocation across Chinese firms in correspondence with the introduction of the stimulus plan in 2009. First, we find that up to 2008, i.e. the pre-stimulus period, the effect of cincreases in credit supply on firm borrowing was larger for firms with higher initial average capital productivity. This result provides micro-based evidence that China has experienced a gradual reallocation of capital from low to high productivity firms up to 2008, which has been considered an important driver of its growth performance in that period. Second, we find that during the stimulus plan years (2009-2010) there was a reversal in the trend of capital allocation across Chinese firms, with an increase in bank credit towards firms with lower initial average product of capital. We show that this reallocation is driven by two forces. First, relative to the pre-stimulus period, more credit flew towards state-owned firms. Our estimates indicate that the effect of credit-supply increase on firm borrowing was 38% larger for state-owned firms relative to private firms in the period 2009-2010. This is consistent with existing evidence that Chinese state-owned firms were still, on average, less productive than private firms at the outset of the stimulus plan.[4] Second, we find that the change in capital allocation towards less productive firms holds also when we focus exclusively on private firms. This is consistent with Bai, Hsieh, and Song (2016), who argue that one of the effects of the Chinese fiscal stimulus program was to channel financial resources towards low-productivity but local-government-favored private firms, with potentially negative effects on the efficiency of capital allocation.[5]

Overall, our results indicate that the reallocation of capital towards low productivity firms during the stimulus period was driven both by a *between effect* – from private to state-owned firms – and a *within effect* – towards the less productive among private companies. We use our estimates to provide a quantification of the relative importance of these two effects, both of which suggest an increase in credit misallocation during the stimulus years. Our estimates indicate that the *between* effect dominates: around 70 percent of the increase in misallocation during the stimulus period was driven by credit reallocation from private firms to SOEs, while 30 percent was driven by capital flowing

[4]Several papers have documented how state-owned firms are, on average, less productive than private firms in China. For example, Song, Storesletten, and Zilibotti (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 average 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)."

[5]As a robustness test, we explore whether our effects are driven by the government's large investments in infrastructure during the stimulus period. Here it is important to notice that our matched dataset does not cover firms operating in the construction and utility sectors, but focuses on those in the manufacturing sector. Therefore our results are unlikely driven directly by the fiscal stimulus. However, it is still possible that our effects are driven by SOEs operating along the production chain of the construction and utilities sectors, such as steel producers. To this end, we show that our results are robust to excluding firms with input-output linkages with the construction and utilities sector.

towards the less productive among private firms.

Finally, we document that the change in the trend of credit allocation between private and state-owned firms did not immediately reverse back at the end of the stimulus years, indicating persistent effects of the stimulus policies.

What can explain the reversal in capital allocation? In the last part of the paper, we discuss and test in the data two main potential mechanisms that can rationalize our empirical findings. The first potential explanation is the role played by state-owned banks in the Chinese financial system. State-owned banks (SOBs) might both have a preferential relationship with state-owned firms (SOEs), and respond more than other banks to the government credit plan. To test this mechanism we reconstruct the ownership structure of China's largest banks. Our results document a special connection between SOEs and SOBs, but we also show there is no correlation between the degree of bank state-ownership and credit growth at bank level during the stimulus years.

Next, we discuss whether higher lending to SOEs during the stimulus period might be driven by implicit government guarantees, which make lenders favor SOEs more when the probability of financial distress increases. Although we cannot directly test this mechanism in the data, we show evidence consistent with it. In particular, we show that while in the pre-stimulus period loans to state-owned firms had a higher probability of becoming non-performing relative to loans to private firms, this gap closes during the stimulus period, consistent with government intervening to avoid state-owned firms entering financial distress. To rationalize this channel, we provide a model that builds on Song et al. (2011). In particular, we model a dynamic economy in which firms are heterogeneous in two dimensions: productivity and state-connectedness, both of which affect their ability to access external finance. Private firms are operated by skilled entrepreneurs, have higher productivity, and rely on both private investments and bank loans to grow; state-connected firms are neoclassical, employ regular workers and in equilibrium only borrow from banks. We add to Song et al. (2011) by explicitly modeling recessions and stimulus, and the implicit government bail-out of state-connected 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 that drives growth in normal times slows down and can potentially reverse. We also show that credit expansions amplify this effect. While China-specific stylized facts certainly motivate the model assumptions, this mechanism applies more broadly and our findings are informative of policy-driven credit expansions in economies characterized by preferential access to finance for government-connected firms.

Related literature

This paper is related to several strands of the literature in macroeconomics and finance. First, it is related to studies that document how misallocation of factors of production across firms can explain a large fraction of the observed differences in aggregate TFP and income across countries (Hsieh and Klenow 2009). As a consequence, an efficient reallocation of resources across heterogeneously productive firms can contribute to economic growth (Restuccia and Rogerson 2008). In fact, this process has been described as one of the forces behind China's fast economic growth in the early 2000s and its large net foreign surplus despite a high rate of return on domestic investment (e.g., Song et al. (2011)). Consistent with this mechanism, Hsieh and Song (2015) document that 83% of state-owned manufacturing firms in 1998 were either shut down or privatized in the next decade, resulting in a partial convergence in labor and capital productivity between surviving state-owned firms and private firms in the period between 1998 and 2007. Our paper contributes to this literature by documenting using detailed micro-data how financial frictions can impact the dynamics of credit allocation across firms in different stages of the business and credit cycle. In support of previous literature, we provide empirical evidence of a gradual reallocation of capital from low to high productivity firms in the years up to 2008. Furthermore, we document that this trend has reversed with the introduction of the stimulus plan.[6]

Our paper is also related to the macro literature on resource allocation over the business cycle. The conventional wisdom in this literature follows the Schumpeterian notion that recessions can ameliorate the underlying allocation of resources absent financial frictions (Caballero and Hammour 1994, Cooper and Haltiwanger 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 (Kiyotaki and Moore 1997), or conclude that recessions are associated with cleansing – albeit excessive – of the least productive matches (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 bad times.[7]

Our paper is also related to Gopinath et al. (2015), that show that, following the adoption of the euro, countries in the South of Europe experienced both an increase in capital inflows and an increase in misallocation of resources across manufacturing firms. Our paper similarly shows that resource misallocation is amplified by credit expansions during bad times, as in the case of the Chinese stimulus plan. A few studies have identified different sources of capital misallocation including community identity (Banerjee

[6]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 credit allocation, especially the efficient reallocation leading up to the stimulus and its reversal driven by the recession and credit expansion.

[7]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.

and Munshi (2004)), size-dependent policy (Banerjee and Duflo (2014)), and political connections (Khwaja and Mian (2005) and in the Chinese context, Brandt and Li (2002), Li, Meng, Wang, and Zhou (2008)). Relative to these studies we contribute by studying how such frictions (in our case, state-connectedness) interact with recession and credit expansion.

Finally, our paper is related to a new wave of research that studies the drivers and consequences of China's credit boom, and in particular the large increases in debt of Chinese local governments and in 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 et al. (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.[8]

Closely linked to China's recent credit boom is the rise of shadow banking. Hachem and Song (2016) and Wang, Wang, Wang, and Zhou (2016) propose theoretical mechanisms for the growth of the sector based on liquidity regulation and interest rate liberalization respectively. Acharya, Qian, and Yang (2016) analyze a proprietary panel data on bank-issued wealth management products and argue that the stimulus plan triggered the unprecedented rapid growth of shadow banking activities in China. Through an alternative mechanism of debt rollover, Chen, He, and Liu (2017) also attribute the growth after 2012 to the massive fiscal stimulus plan.

Our paper focuses on an aspect so far overlooked by this recent literature: China's stimulus package not only involved pursuing both fiscal stimulus in the form of large government spending, but also 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 local government financing vehicles. The credit stimulus therefore not only facilitated financing local government spending through LGFVs – traditionally operating in the construction and utilities sectors –, but also had a broader impact on the Chinese economy. Closely related to our paper is Ho, Li, Tian, and Zhu (2017), which uses a proprietary loan-level dataset from a state-owned bank in one prefectural-level city. The paper exploits the policy announcement of the fiscal stimulus to show that this policy intervention resulted in credit misallocation between state-owned enterprises and private firms. It complements our study by providing evidence that credit misallocation was in part driven by bank risk management practices favoring SOEs, which is one manifestation of the mechanism we propose. Our comprehensive data covering 19 banks and longer

[8]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).

horizon allow us to go beyond state-owned banks, isolate credit supply forces, and study allocation dynamics.

While our paper draws evidence from China, the insights apply more broadly to credit expansions, liquidity injections, and stimulus programs that have been introduced in many countries. It is particularly related to the 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.[9]

The rest of the paper is organized as follows. Section 2 provides the institutional background, highlights the main features of China's stimulus plan, and provide a set of stylized facts from both aggregate and micro-level data. Section 3 describes the data sources. Section 4 discusses the identification strategy and Section 5 presents the main empirical results, and discusses a set of potential mechanisms that can rationalize our empirical findings.

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 2 illustrate the structure of the economic stimulus plan. In what follows we describe it in detail.

The fiscal part of the stimulus plan, officially announced on November 9 of 2008, prominently featured spending 4 Tr RMB (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 RMB – around one-third of the stimulus plan – using government budget and treasury bonds. The remaining 2.82 Tr RMB – more than 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.[10]

[9]See, among others, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Kashyap and Stein (2000) for general intervention impacts, and more recently Brunnermeier, Sockin, and Xiong (2017, 2016), Hachem and Song (2016), and Bleck and Liu (2014). Also broadly related are studies on "zombie lending" (e.g., Peek and Rosengren (2005); Caballero, Hoshi, and Kashyap (2008)) and crony capitalism (e.g., Zingales (2014); Bai, Hsieh, and Song (2014)).

[10]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

In parallel, the Chinese government encouraged an increase in credit supply to the real economy by banks. Due to the late start of equity markets, bank credit has traditionally been the dominant form of external financing in China, especially for unlisted firms which are the majority in our data. Typically, the government manages bank credit supply through setting loan quotas, deposit and lending rates, and required reserve ratios.[11] Total loan quotas, which are the lending targets for commercial banks that bank officials are encouraged to meet, were increased from \$4.9 trillion RMB in 2008 to almost \$10 trillion RMB 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. The two most prominent measures in this sense were the following. 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 small banks, and from 17.5% to 15.5% for large banks.[12] Second, the PBoC reduced the base one-year lending rate from 7.47% to 5.31%.[13]

One of reasons behind the changes in banking regulation was to meet LGFVs' borrowing needs. Bai et al. (2016) and Chen et al. (2017) 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, we emphasize that the credit expansion had a broader impact on the Chinese economy beyond supporting LGFVs, whose investment are primarily concentrated in the construction and utility sectors. Section 2.2.3 provides direct evidence of this starting from loan-level data.[14] In what follows we present a set of stylized facts using

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.

[11]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.

[12]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.

[13]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.

[14]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 RMB investment. This is a total misunderstanding." 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 RMB, among which LGFVs received around 2.3 trillion, the

both aggregate and micro data consistent with the above description of the stimulus plan.

2.2 Stylized Facts

2.2.1 Credit Boom: Aggregate Data

We start by presenting a set of simple stylized facts on the credit stimulus using aggregate data. Figure 1 shows the aggregate credit flow to the real economy according to official data from the PBoC, the central bank of China. The aggregate credit flow is calculated as the annual change in the outstanding exposure of Chinese households and firms to the financial system. The data cover the years between 2002 and 2015 and are divided into five source of external finance: bank loans, equity, corporate bonds, several types of off-balance sheet lending which we group under "shadow banking", and other types of financing.[15] There are two main stylized facts that emerge from Figure 1. First, bank loans represents the largest source of external finance in China. On average, aggregate bank loans represent 72% of the aggregate credit flow to the real economy between 2002 and 2015. This share has been decreasing in recent years due to the large increase in the corporate bond market and shadow banking, but still represents 61% of aggregate credit flows on average in the years after 2010. Second, bank lending to the real economy increased substantially between 2008 and 2009, at the outset of the stimulus program. In particular, outstanding bank loans to Chinese households and firms increase by 10.5 Tr RMB in 2009, against the 5.1 Tr observed in 2008 and 4 Tr RMB observed in 2007.

2.2.2 Changes in Bank Regulation

The increase in bank credit documented in Figure 1 is consistent with the measures introduced by the central bank of China 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 as a share of their deposits 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

non-residential non-LGFV sector received 1 trillion, and the residential sector received 1.4 trillion.

[15] 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-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.

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, the 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 freed liquidity that became available for lending. Consistently with this argument, Figure 4 shows that banks with larger reserve ratio in the pre-stimulus period experienced larger increase in credit during the stimulus years.

In the same period, the central bank of China lowered its benchmark lending rates for loans of different maturities. Benchmark rates are lower bounds on interest rates that commercial banks are allowed to 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.[16] The Figure shows that (i) interest rates 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.

2.2.3 Credit Boom: Micro-data

Next, we document that our micro-data reflects the increase in aggregate bank lending reported in Figure 1. In addition, we provide new stylized facts on the allocation of bank credit across sectors during the stimulus years of 2009 and 2010. Our micro-data comes from two sources: the Chinese Banking Regulatory Commission and the Annual Survey of Industrial Firms. Both datasets are described in detail in Section 3.

We start from the Chinese Banking Regulatory Commission loan-level dataset. Figure 5 reports the quarterly change in aggregate outstanding bank loans to Chinese firms, as well as its decomposition across sectors. As shown, Chinese banks substantially increased their lending to firms starting from the first quarter of 2009, right after the introduction of the stimulus program in the last quarter of 2008. On a quarter-to-quarter basis, Chinese banks' outstanding loans to firms increase by 2.42 Tr RMB in the first quarter of 2009, against 0.97 Tr RMB in the first quarter of 2008 and 0.63 Tr RMB in the first quarter of 2007. On a year-to-year level, outstanding bank loans to firms increased by 5.6 Tr RMB in 2009, more than twice the observed increase in the two previous years.[17]

[16]The loan-level data from the CBRC used in the empirical analysis does not report information on interest rates.

[17]The annual increase in outstanding bank loans to firms in the CBRC data is 1.9 Tr RMB for 2007

The loan-level data from the CBRC report the sector of operation of the borrower, allowing us to separate the increase in bank lending observed in the stimulus years among different sectors. We categorize borrowers in four main sectors: agriculture and mining, manufacturing, construction and utilities, and services. Figure 5 shows that the increase in bank lending during the stimulus years affected firms in all sectors. Maybe contrary to public perception that bank lending was primarily directed to the construction sector, the largest increases in bank lending occurred in manufacturing and services. The credit stimulus plan therefore had a widespread impact on the real economy also outside of financing investment by local government financing vehicles, which tend to operate in the construction and utilities sector.

The second source of micro-data used in the empirical analysis is the Annual Survey of Industrial Firms. Figure 6 shows the yearly change in aggregate long-term liabilities of manufacturing firms covered in the survey. As shown, there is a sharp increase in long-term liabilities during the stimulus in both 2009 and 2010.

3 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 (ASIF) of the China's National Bureau of Statistics. In what follows we describe in more details each of these datasets, as well as our data cleaning and merging procedures.

The CBRC database reports information on loans originated by the 19 largest Chinese banks in the period between October 2006 and June 2013. The data is collected monthly by the Chinese Banking Regulatory Commission. Banks are required to transmit to the regulator information on all loans issued to borrowers whose annual outstanding balance is equal or above 50 million RMB. The dataset covers around 80% of total outstanding loans to Chinese companies. The raw data comes at loan-month level. In the empirical analysis we aggregate the data at either bank-firm level or at firm level. Table 1, Panel A, reports main summary statistics from the CBRC data. As shown, the average outstanding loan balance at bank-firm level in the CBRC data is 163 million RMB (179 million RMB if we just focus on the stimulus years). Crucially, the CBRC 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 ASIF database covers firms operating in the manufacturing sector from year 1998 to 2013. All firms with annual sales above a given monetary threshold are surveyed,

and 2.2 Tr RMB for 2008. Comparing Figure 5 with Figure 1 shows that the CBRC loan-level data captures around half of the total increase in outstanding bank loans to the real economy in 2009 and 2010 as reported by the central bank. In this sense, it is important to remember that Figure 1 reports aggregate bank lending to both firms and households, while the CBRC data reported in Figure 5 only captures lending to firms.

making this effectively a census of medium to large size Chinese firms. This threshold was set at 5 million RMB (730,000 USD) until 2010, and then raised to 20 million RMB (3 million USD) from 2011 onward.[18] The main firm-level variables of interest in our empirical analysis are number of employees, total fixed assets, and ownership status. We use annual changes in total fixed assets as a share of value of production as a proxy for investment. Another key variable in our analysis is state ownership. The ASIF reports the legal registration status of each firm, such as "privately owned" or "state-owned". However, as underlined by Hsieh and Song (2015), this definition does not take into account that: (i) firms that have been privatized can be still registered as state-owned, and (ii) firms legally registered as private can be ultimately controlled by a state-owned company. Therefore, in the empirical analysis we use as our preferred measure of state-ownership the share of registered capital effectively owned by the government. We apply two restrictions to the initial sample covered by the ASIF dataset. First, we focus on firms with non-missing data for year-to-year changes in labor and capital (fixed assets) during the period under study, as these are our real outcomes of interest. Second, to deal with the change in reporting threshold and insure consistency of the sample over time, we focus on firms with annual sales above 20 million RMB.

While the ASIF database has a broad coverage of firms in the manufacturing sector in China, including many small firms, the CBRC database covers only borrowers with annual outstanding balance equal or above 50 million RMB. Thus, the matched ASIF-CBRC sample used in our regressions focuses on relatively large manufacturing firms. Given the focus on large firms, our matched sample represents 63 percent of total liabilities, 45 percent of tangible assets and 21 percent of employment of all manufacturing firms covered by ASIF during the stimulus years.

Table 1, Panel B reports the main summary statistics for the matched sample. Notice that these summary statistics refer to the stimulus years 2009 and 2010. As shown, Chinese manufacturing firms with outstanding bank debt equal or above 50 million RMB are relatively large. The average number of employees is 2,144 and the average annual sales are 1.6 Bn RMB. Despite the focus on large firms, there is variation in the data. Half of the firms in our matched dataset have less than 702 employees and less than 421 million RMB in annual sales. On average, around 11% of the firms in our matched sample are at least 50% state owned, and 44% have positive sales outside of China. Finally, only 5.2% of matched firms in our data are publicly traded in the Chinese stock market.

[18]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.

4 Identification Strategy

In this section we describe our identification strategy. The objective of our empirical analysis is twofold: (1) to identify the effect of the credit-supply increase by Chinese banks during the stimulus years on firm borrowing, investment and size; (2) to study how the increase in credit supply was allocated across firms, with particular attention to heterogeneous effects across firms with different levels of connection to the central government. 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-level exposure to bank credit-supply increases generated by the stimulus plan. Similarly to Chodorow-Reich (2014), our identification strategy exploits variation in bank lending at national level to construct a firm-specific measure of exposure to credit supply changes.[19] Specifically, we construct the following measure of firm-level exposure:

$$\Delta \widetilde{L_{icjt}} = \sum_{b \in O_i} \omega_{bi,t=0} \times \Delta \log L_{b-cj,t} \quad , \tag{1}$$

where b indexes banks, i firms, c cities, j sectors and t time. The variable $\Delta \log L_{b-cj,t}$ is the change in the logarithm of the aggregate loan balance of bank b between year $t-1$ and t to all borrowers excluding those located in the same city as firm i and those operating in the same sector as firm i. This allows us to remove from our measure of exposure any potential correlation in demand shocks at both location-level and industry-level. The weights $\omega_{bi,t=0}$ capture the strength of the relationship between firm i and bank b in the initial period.[20] 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).

In words, Equation (1) 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.[21] First, borrower-lender relationships have to be persistent over time such that firms can not easily switch from one lender to another. Second, the cross-sectional variation in bank lending during

[19] 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.

[20] 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.

[21] 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).

the stimulus years reflects only supply forces or observable borrowers' characteristics, but is uncorrelated with unobservable borrowers' characteristics that affect their credit demand. In what follows we discuss our identification assumptions in more detail.

Discussion of Identification Assumptions

The first identification assumption is that bank-firm relationships are persistent over time. If firms can easily reshape their portfolio of lenders, then variation in $\Delta \widetilde{L_{icjt}}$ cannot fully explain variation in actual firm borrowing. We test this assumption in Table 2. The outcome variable in this table is a dummy equal to 1 if firm i takes a new loan from bank b at time t. Each observation in the dataset is a potential bank-firm relationship. That is, for each firm and year, we create a potential match of each firm with each potential lender. The independent variable is a dummy capturing a pre-existing banking relationship. This dummy is equal to 1 if firm i has a credit relationship with bank b at time $t-1$. The results reported in Table 2 show that bank-firm relationships are extremely persistent in China, both when we consider all years covered by the CBRC loan-level data (2006 to 2013) and when we focus on the stimulus years (2009 and 2010). The estimated coefficients reported in column 1 and 2 indicate that, provided a firm takes a new loan from a bank, the probability of getting the new loan from a bank with which the firm had a pre-existing credit relationship is 95%.

The second key assumption for our identification strategy to be valid 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. Among the 19 banks covered by the CBRC loan-level data, the average increase in outstanding loan balance between 2008 and 2009 was 44%, and ranged from 17% to more than 100%. 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, 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 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 changes in global demand. Additionally, we control for city fixed effects to capture policies that specifically target certain areas in this period, such as the large federal transfers to the Sichuan region after the 2008 earthquake. Finally we add a dummy capturing whether the firm is publicly traded, as well as standard firm controls such as age and size.

Table 3 reports the coefficient on $\Delta \log L_{b-cj,t}$ when the outcome variable is lending by bank b to firm i. As shown, 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), and when focusing on the stimulus years (columns 5 and 6).

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:

$$\Delta \log loan_{ibcjt} = \alpha + \alpha_{it} + \beta \Delta \log L_{b-cj,t} + \varepsilon_{ibt} \tag{2}$$

Where the outcome variable $\Delta \log loan_{ibt}$ 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 (2) 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 (2) are also reported in Table 3. Column 4 shows the results using all years for which loan-level data is available (2006 to 2013), while column 8 reports the results when focusing on the stimulus years 2009 and 2010. As shown, the estimated coefficients on $\Delta \log L_{b-cj,t}$ 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 column 3 for the specification estimated on all years, and column 7 for the stimulus years, conditioning the sample to the same set of firms borrowing from multiple lenders used to estimate Equation (2). Notice that, 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.[22] Therefore, the coefficients reported in Table 3 support the validity of our identification strategy.

[22] The assumption is that bank exposure and firm characteristics have to be additively separable in the underlying model describing borrowing of firm i from bank b (Khwaja and Mian 2008 and Chodorow-Reich 2014).

5 Empirical Results

In Section 2.2, we documented a set of basic stylized facts that emerge from micro data. In particular, loan-level data show a sharp increase in bank lending to Chinese firms starting from the first quarter of 2009, immediately after the introduction of changes in bank regulation aimed at increasing credit supply to the real economy in the last quarter of 2008. In addition, firm-level data show that Chinese manufacturing firms experienced a sharp increase in long-term debt during the two years of the stimulus plan (2009 and 2010). The timing of the increase in bank loans and long-term debt 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 4 to plausibly identify the effect of changes in credit supply on firm level outcomes.

To this end, we proceed as follows. First, in Section 5.1, we present the average effects of credit supply on firm level borrowing, investment and employment. Second, in Section 5.2, we study the allocation of credit across firms by interacting our measure of exposure to credit supply shocks with initial firm characteristics. In this step we are particularly interested in investigating whether banks allocated funds differently before and after the introduction of the stimulus plan. Section 5.3 reports in greater detail the dynamics of real effects and ex-post loan outcomes. Finally, in Section 5.4 we discuss in detail and, whenever possible, test in the data a set of potential mechanisms that can rationalize our empirical findings on how credit allocation has evolved in China over time.

5.1 Average Effects of Credit Supply on Firm-Level Outcomes during Stimulus

We start by studying the average effects of bank credit-supply increases on firm-level outcomes during the stimulus years of 2009 and 2010. The baseline equation that we estimate is as follows:

$$\Delta \log y_{icjt} \quad = \quad \alpha_c + \alpha_j + \alpha_t + \beta \Delta \widetilde{L_{icjt}} + \gamma X_{i,t-1} + \varepsilon_{icjt} \tag{3}$$

where $\Delta \log y_{ijct}$ is the change between year $t-1$ and year t in the log of outcome y of firm i, operating in industry j and city c. We focus on three main outcomes at firm-level: bank loan balance, physical capital and employment. The loan balance of firm i is computed by summing the outstanding loan balance across all lenders of firm i in a given year. Our proxy of physical capital is the book value of fixed assets, while employment is computed as average number of workers. The coefficient of interest is β, which captures the effect of bank credit supply on firm-level outcomes. The variable $\Delta \widetilde{L_{icjt}}$ is defined as described in Equation (1). Finally, we augment the model with sector and city fixed effects, and control for a set of firm characteristics ($X_{i,t-1}$) including export status, size, age, and a dummy capturing if the firm is publicly traded. Given the role played by local politics and the geographical specialization of economic activity across Chinese regions, we assume that model errors are correlated across firms operating in the same location and cluster standard errors at city or prefecture-level city level in all regressions (330 clusters).

Table 4 reports the results of estimating Equation (3) when the firm-level outcomes are the change in firm borrowing, investment and employment growth. The results refer to the stimulus years: 2009 and 2010. The estimated coefficients reported in columns 1 and 2 show that firms with larger exposure to bank credit supply experienced a larger increase in firm borrowing. In terms of magnitude, the estimated coefficient in column 2 – our preferred specification – indicates that a one percent increase in credit supply from pre-stimulus lenders translate into an increase in firm borrowing of similar magnitude. Notice that both magnitude and precision of the estimated coefficient are stable to adding controls for borrower characteristics.[23]

Next, we study the effect of bank credit supply increases on real outcomes. Our results show that firms with higher exposure to credit supply increases due to their pre-existing banking relationships experienced not only larger increases in bank loans, but also larger investment and employment growth during the stimulus years. The estimated coefficients reported in columns 4 and 6 indicate that firms with one percent larger increase in credit supply experienced a .1 percentage points larger increase in investment as a share of value of production and .3 percent larger increase in employment.

5.2 Credit Allocation Across Firms and Over Time

The objective of this section is to study how credit allocation across firms has evolved in China over time. For this purpose, we first study credit allocation across firms in the stimulus years and then extend our identification strategy to all the years in our dataset (2006 to 2013), which covers both the period before and the period after the introduction of the stimulus plan at the end of 2008.

5.2.1 Credit Allocation during the Stimulus Years

We begin by studying the allocation of bank credit across firms during the stimulus years 2009 and 2010. To this end, we estimate the following version of Equation (3):

[23] Table A1 in the Appendix shows additional evidence on the average effect of bank credit supply on loan-level outcomes. In particular, Table A1 shows that firms with larger exposure to bank credit supply experienced an increase in the average maturity of new loans received during the stimulus years. The magnitude of our estimated coefficients indicate that a one standard deviation increase in exposure to bank credit supply translates into 0.8 months higher maturity.

$$
\begin{aligned}
\Delta \log y_{icjt} &= \alpha_c + \alpha_j + \alpha_t + \beta_1 \Delta\widetilde{L_{icjt}} + \beta_2 C_{i,t=0} + \beta_3 \Delta\widetilde{L_{icjt}} \times C_{i,t=0} \\
&+ \gamma X_{i,t-1} + \varepsilon_{icjt} \qquad (4)
\end{aligned}
$$

where the variable $C_{i,t=0}$ is a pre-determined firm characteristic and captures, depending on the specification, either the initial average product of capital of firm i or its share of state-ownership, both defined in the pre-stimulus period. The coefficient of interest is β_3, which captures the differential effect of exposure to bank credit supply on firm borrowing depending on initial firm characteristics.

We start by studying the effects of credit supply on firm-level outcomes for firms with different average product of capital (APK). Columns (1) and (2) of Table 5 report the results of estimating Equation (4) when $C_{i,t=0}$ is equal to the firm-level APK in the pre-stimulus period. APK is defined as the log of industrial value added divided by book value of fixed assets and it is used here as a proxy for marginal product of capital. The outcome variable is year-to-year change in borrowing at firm level.

As shown, the estimated coefficient on the initial average product of capital is positive and statistically significant, which is to be expected as initial APK captures to a large extent credit demand. However, the estimated coefficient on the interaction between credit-supply increases and initial average product of capital is instead negative and statistically significant. This indicates that, during the stimulus years, the effect of credit supply on firm borrowing was larger for firms with lower pre-stimulus average product of capital. The magnitude of the estimated coefficient β_3 indicates that firms with a 1 standard deviation larger APK experienced a 6 percent lower increase in bank loans during the 2009-2010 period.

What drives this difference? Several papers have documented that state-owned firms have, on average, lower productivity than private firms in China (Song et al. 2011, Brandt et al. 2005, Hsieh and Song 2015). Figure 7 documents this stylized fact in our data by showing the distribution of APK in 2007 for SOEs and Private firms. Thus, we investigate whether credit allocation towards low capital productivity firms during the stimulus period was driven by higher credit allocation towards state-owned firms or towards less productive firms more generally. To this end, in columns (3) and (4), we split our sample between fully private firms and firms with positive government ownership. The estimated coefficients document two important results. First, we find that state-owned companies received more bank credit than privately owned companies. This can be seen by comparing the estimated coefficients on $\Delta\widetilde{L_{icjt}}$ (β_1) in columns (3) and (4). Second, among private firms, we find that those with lower initial capital productivity received more credit during the stimulus years (see column (3)). This latter result is consistent with Bai et al. (2016), that argue how one of the effects of the Chinese fiscal stimulus program was to channel financial resources towards low-productivity but local-government-favored private firms, potentially due to corruption or political favoritism. When we focus on SOEs, instead, initial capital productivity does not affect credit allocation, suggesting that SOEs benefited from the increase in credit supply independently from their initial productivity. Finally, in column (5), we report the results obtained by estimating Equation (4) when $C_{icj,t=0}$ is the initial share of state ownership of firm i. The estimated coefficient on the interaction (β_3) is positive and statistically significant. The magnitudes indicate that, in response to a 1 standard deviation change in credit supply, fully state-owned firms experienced a 15.7 percent increase in borrowing, versus the 11.3 percent increase for fully private firms during the stimulus years, i.e. the effect of credit supply on firm borrowing was 39% larger for state-owned firms relative to private firms.[24] Notice that this result holds controlling for firm initial productivity, indicating that preference for SOE in credit allocation is independent from productivity.

Overall, the results presented in Table 5 show that the reallocation of capital towards low productivity firms during the stimulus period was driven by two effects: a *between* effect – from private to state-owned firms – and a *within* effect – towards the less productive among private firms. Both results suggest an increase in credit misallocation during the stimulus years. We can use the estimates presented in Table 5 to provide a quantification of the relative importance of the *between* and *within* effects. To this end, we proceed in two steps. First, we compute the gap in average product of capital with respect to high productivity private firms for both SOEs and low-productivity private firms.[25] These productivity gaps capture the potential increase in output that could be obtained by reallocating a unit of capital from SOEs to high productivity private firms, or from low to high productivity private firms. Second, we compute the difference in credit growth with respect to high productivity private firms experienced by SOEs and low productivity private firms during the stimulus years.[26] Finally, we multiply the productivity gaps by the difference in credit growth, and weight the numbers obtained by the initial amount of outstanding bank loans of SOEs and low productivity private firms. This calculation suggests that 70 percent of the increase in misallocation during the stimulus period is driven by the *between* effect – from private firms to SOEs – and 30 percent is driven by the *within* effect – capital flowing towards the less productive private firms.

A potential concern with the results presented in Table 5 is the role played by govern-

[24]Notice that this quantification does not take into account the fact that SOEs might act as financial intermediaries and issue loans to private companies. This is because our data does not cover entrusted loans that Chinese firms can make to each other. Still, we believe this is not a concern during the stimulus period given that the size of Chinese shadow banking at the time was still limited (see Figure 1).

[25]To compute these gaps we first split private firms into high and low capital productivity using the median average product of capital before the stimulus years. The productivity gaps with respect to high productivity private firms are equal to 1.62 for SOEs and 1.89 for low-productivity private firms.

[26]Notice that Table 5 indicates that, during the stimulus years, both low productivity private firms and SOEs experienced larger credit growth relative to high productivity private firms. These differences are equal to 35 percent for SOEs and 11 percent for low-productivity private firms.

ment investments in infrastructure during the stimulus period. For example, SOEs might be more likely to operate in sectors directly affected by higher government expenditure – e.g. construction and utilities – or, within those sectors, to be the "favored" recipients of government contracts. In this respect, it is important to notice that our matched dataset does not cover firms operating in the construction and utility sectors, but focuses exclusively on manufacturing. Nonetheless, it is still possible that our effects are driven by SOEs operating along the production chain of the construction and utilities sectors, such as steel producers.

To rule out the confounding effect of government expenditure shocks, we show that our results are robust to excluding firms that operate along the production chain of sectors plausibly affected by government induced demand shocks during the stimulus period. To this end, we use the OECD Input-Output Tables for China to identify those sectors whose output has higher elasticity to unit increase in final demand in either construction or electricity, gas and water supply. Next, we replicate Table 5 excluding firms operating in sectors in the top decile in terms of output elasticity. These include firms operating in the production of basic metals (iron, steel, and non-ferrous metals) and non-metallic mineral products, as well as firms operating in mining and quarrying.[27] Table A2 in the Appendix reports the results. As shown, the point estimates obtained by excluding firms with plausible higher demand driven by input-output linkages during the stimulus period are very similar in magnitude to those obtained in our main specification. This indicates that heterogeneous shocks from government investment in infrastructure during the stimulus years are not driving our results. We interpret the similar magnitude of the estimated coefficients obtained with and without firms operating along the production chain of construction and utilities as an additional validation of our identification strategy.

5.2.2 Credit Allocation before and after the Stimulus Plan

Next, we apply our identification strategy to all years in our sample to study how credit allocation across firms has evolved over time. To this end, we estimate a panel version of Equation 4 which aims at identifying the different role of productivity and state-ownership in the allocation of capital in three different periods: the pre-stimulus years 2006 to 2008, the stimulus years 2009 and 2010, and the post stimulus years 2011

[27] More specifically, sectors in the top decile of output elasticity to unit increase in final demand of construction and utilities are those identified by the following codes in the Chinese industry classification system: B06, B07, B08, B09, B10, B11, C32, C33.

to 2013, as follows:

$$
\begin{aligned}
\Delta\log y_{icjt} &= \alpha_c + \alpha_j + \alpha_t \\
&+ \beta_1 \Delta\widetilde{L_{icjt}} \times C_{i,t=0} + \beta_2 \Delta\widetilde{L_{icjt}} \times C_{i,t=0} \times I(stimulus) + \beta_3 \Delta\widetilde{L_{icjt}} \times C_{i,t=0} \times I(post) \\
&+ \beta_4 \widetilde{L_{icjt}} \times I(stimulus) + \beta_5 \widetilde{L_{icjt}} \times I(post) \\
&+ \beta_6 C_{i,t=0} \times I(stimulus) + \beta_7 C_{i,t=0} \times I(post) \\
&+ \beta_8 \widetilde{L_{icjt}} + \beta_9 C_{i,t=0} + \gamma X_{i,t-1} + \varepsilon_{icjt} \qquad (5)
\end{aligned}
$$

As in the previous specification, the outcome variable is the change in firm borrowing. We use triple interactions to capture the differential effect of exposure to bank credit supply on firm borrowing depending on initial firm characteristics and time period. The dummy $I(stimulus)$ indicates the years 2009 and 2010, $I(post)$ indicates the years 2011 to 2013.

We start by estimating Equation (5) when $C_{i,t=0}$ is the initial average product of capital of each firm. In this specification, the coefficients β_2 and β_3 isolate the differential effect of capital productivity in the stimulus period and in the post-stimulus period, both relative to the excluded interaction – the pre-stimulus years (2006 to 2008) – which is captured by β_1. The specification includes the main effects of the interaction as well as other firm characteristics.

Columns (1) to (3) of Table 6 report the results using all firms in our sample. The estimated coefficient β_1, which captures the heterogeneous effects in the pre-stimulus period, is positive and significant. This indicates that, up to 2008, more productive firms received more bank credit. This result provides direct empirical evidence of the process of capital reallocation from low-productivity (predominantly state-owned) to high-productivity (predominantly private) firms in the pre-stimulus years, which is often mentioned as one of the driving forces of China's growth in the 2000s (Song et al. 2011). However, consistent with the results shown in Table 5, this effect reversed starting from 2009, when capital began flowing towards initially less productive firms. This result is robust to the inclusion of firm observable characteristics (column (2)) and firm fixed effects (column (3)).

Next, we test these heterogeneous effects separately for SOEs and private firms in columns (4) and (5). As in Table 6, our estimates indicate that initial firm productivity is not a significant factor in capital allocation when we focus exclusively on SOEs. Instead, initial product of capital affects capital allocation among private firms: positively in the pre-stimulus period, negatively after the introduction of the stimulus plan.

Finally, in column (6), we estimate a version of Equation (5) where $C_{i,t=0}$ is the share of state-ownership of each firm. The objective is to formally test whether the change in capital allocation from high to low productivity firms started with the stimulus period maps into a change in capital allocation from private to state-owned companies. The results are consistent with a shift towards SOEs after 2008. The coefficient on the interaction between credit supply changes and state-ownership (β_1), which captures the pre-stimulus period, is negative and strongly significant. This indicates that, up to 2008, higher credit supply had a larger effect on borrowing for private firms than for state-owned firms. Instead, the estimated coefficient β_2 is positive and statistically significant. This indicates a reversal in credit allocation after the introduction of the stimulus plan.[28] Finally, our results suggest that the shift in credit allocation towards SOEs did not reverse back at the end of the stimulus years. In particular, the estimated coefficient β_3 is also positive and significant, which indicates that the effect of the stimulus plan on credit allocation extended outside of the 2009-2010 period.[29]

5.3 Real Effects and Ex-post Loan Outcomes

In this section we focus on firm real outcomes as well as ex-post loan performance. Table 7 reports the results of estimating a version of Equation (5) where the outcome variables are firm investment (Panel A), employment growth (Panel B), and a variable indicating whether loans to firm i have eventually become delinquent (Panel C). For each outcome, we report the same six specifications as for firm borrowing in Table 6.[30]

In Panel A, we first study the heterogeneous effects on firm investment by initial capital productivity and time period. Firm investment is defined as the year-to-year change in fixed assets divided by (lagged) firm value of production. Our baseline specifications (column (1) to (3)) show that capital investment followed a similar pattern as bank credit. In particular, firms with lower capital productivity started investing relatively more than firms with higher capital productivity during the stimulus period. This indicates an increase in misallocation not only of bank credit but also of physical capital. Columns (4) and (5) show that these heterogeneous effects are mostly driven by differences in investment *between* SOEs and private firms, rather than by variation *within* SOEs or private firms. This is confirmed in column (6) which directly estimates heterogeneous effects on investment by initial state-ownership and time periods.

Panel B studies heterogeneous effects on employment growth for firms with different initial product of capital in each period. Overall, we find no heterogeneous effects either in the pre-stimulus or in the stimulus periods (firms with higher initial APK seem however to experience larger employment growth in the post stimulus period). This result remains when we look at heterogeneous effects by productivity within SOEs and private firms separately. Column (6) suggests that variation in employment growth is better explained

[28]Notice that the magnitude of the differential effect of state-ownership on firm borrowing during the stimulus years is consistent with the estimate reported in Table 5. The sum of estimated coefficients β_1 and β_2 gives the estimated coefficient on the interaction in Table 5.

[29]The estimated coefficients β_2 and β_3 are not statistically different from each other: the t-stats on the difference is 0.56.

[30]All the main effects of Equation (5) are included but not reported to make the table easier to read.

by variation in firm ownership during the stimulus period. The effect of credit supply on employment during the stimulus period was significantly larger for SOEs relative to private firms, consistently with their mandate to preserve employment in bad times.

Finally, in Panel C, we investigate the heterogeneous effects on ex-post loan performance. The outcome variable NPL_{it} is the value-weighted share of loans originated in year t to firm i which eventually become non-performing. The China Banking Regulatory Commission considers a loan as non-performing when it is at least 90 days delinquent after its due date. As a sanity check on this outcome, Table A3 in the Appendix shows the correlation between NPL_{it} and a set of firm characteristics.[31] It shows that, on average, loan default at firm level is positively correlated with state ownership, and negatively correlated with average productivity of capital, firm sales, export status and a dummy capturing publicly traded firms.

Let us now discuss the results reported in Panel C. Our baseline specifications (columns (1) to (3)) show that, in the pre-stimulus years, loans to firms with higher productivity had, on average, lower ex-post default rates. However, starting from 2009, this gap in ex-post loan performance between high and low productivity firms started to close, as seen by comparing the magnitude of the estimated coefficients β_1 and β_2. Columns (4) and (5) show that the same patter holds within private firms, while it is not statistically significant within SOEs. Finally, column (6) reports heterogeneous effects by state-ownership across periods. The results in column (6) indicate that, in the pre-stimulus period, credit supply changes generated higher ex-post default rates among state-owned firms relative to private firms. The gap in ex-post loan performance between SOEs and private firms closed starting from the stimulus years.

These results are consistent with an increase in the importance of state-connectedness during the stimulus years. They might have favored low-productivity but state-connected private firms as well as government-owned firms. For example, state-connected private firms might have gotten easier access to refinancing during bad times because of their political connections. As for SOEs, government guarantees can manifest themselves indirectly through banks willingness to refinance their old loans, or directly through government intervention in providing liquidity (thus avoiding loan default). We next discuss this channel in more detail.

5.4 Discussion

The results presented in Section 5 reveal two main patterns about the dynamics of credit allocation across manufacturing firms in China. First, bank credit moved towards high productivity firms during the boom years of the 2000s. Second, we show that, after the introduction of the stimulus plan, this process has reversed and credit growth has

[31]The sample of firms is the same used in the empirical analysis and all correlations are net of year, industry and city fixed effects.

been relatively higher for low productivity firms. We also showed that state-ownership played an important role in this shift in credit growth. What can explain this reversal in capital allocation? In this section we discuss in detail two potential mechanisms that can rationalize our empirical findings.

5.4.1 State-Ownership Connection

The first mechanism that can rationalize our empirical findings is the role of state-owned banks in the Chinese financial system. This mechanism relies on two empirically testable hypothesis. First, Chinese state-owned banks (SOBs) might have a preferential lending relationship with state-owned firms (SOEs). Although there is scarce direct empirical evidence for China, preferential lending by state-owned banks to politically connected firms – and its real effects – has been documented in other countries (Sapienza 2004, Carvalho 2014) and plausibly applies also in the Chinese context. The second argument is that SOBs might be more willing to respond to the government-sponsored credit plan relative to private banks. This could be either because of direct government influence on bank lending decisions, or could operate indirectly through the career incentives of the bank top management. Notice that if both these hypothesis are verified in the data – preferential lending from SOBs to SOEs and higher responsiveness of SOBs to the credit plan – the state-ownership connection mechanism could explain why more of new credit during the stimulus years was directed to SOEs. Notice that this argument is consistent with a credit supply interpretation of our results.

To test this mechanism, we build a new hand-collected dataset that reconstructs the ownership structure of China's 19 largest banks based on their annual reports. Our measure of state-ownership is the sum of the ownership share of financial institutions under the direct control of the central government (e.g. Central Huijin Investment Ltd), funds under the control of local governments, and state-owned firms. Then, for each bank, we construct the value weighted share of their lending portfolio allocated to SOEs. Figure 8 shows that a higher government share in bank ownership is positively correlated with a higher share of a bank lending portfolio allocated to SOEs.[32]

Next, we test whether banks with higher government ownership in 2008 responded more to the stimulus plan. Figure 9 shows there is no correlation between initial government ownership and credit growth during the stimulus plan: the estimated slope is negative and marginally significant. To summarize, we do find empirical evidence that larger government ownership at bank level is correlated with higher average state-ownership of the borrowers. However, in our sample covering the 19 largest banks in China, we do not find evidence that the responsiveness to the credit plan was primarily driven by bank state-ownership.

[32] The data in Figure 8 refers to year 2008, before the introduction of the stimulus plan. However, this positive relationship is strong in any year of our sample.

5.4.2 Implicit Government Guarantees

The second potential mechanism that can rationalize our empirical findings is that higher lending to SOEs and low-productivity firms during the stimulus period might be driven by implicit government guarantees (broadly interpreted) on bank loans made to state-connected firms. Implicit government guarantees give them easier access to credit: state-connected firms are not constrained by limited pledgeability of their future cash flows because the government can supply additional assets and collateral. Moreover, implicit government guarantees imply that when SOEs are close to financial distress, there is an expectation that the government would step in, perhaps under the justification that these firms are instrumental in preserving employment, especially during recessions. State-connected firms may receive a similar "guarantee", though more "implicit" through favorable treatment by local officials. For simplicity, in our model we refer to all state-connected firms as SOEs and the non-connected firms as private firms. Conditional on firm productivity, implicit government guarantees should push lenders to favor state-connected firms relative to other firms out of bankers' career concerns or considerations of personal costs, and more so when the probability of financial distress increases.[33] 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. However, China Eastern obtained a capital injection of 7 billion RMB 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, defaulted on its debt, and was declared bankrupt in August 2009.

Such frictions are well-recognized in the literature (e.g., Song et al. (2011) and Chang, Liu, Spiegel, and Zhang (2017)), and consistent with the results on ex-post loan performance presented in section 5.3. However, we cannot directly test this explanation in our data. Therefore we instead rationalize this mechanism in an extension of the model by Song et al. (2011), and refer to Ho et al. (2017) for empirical evidence. A formal description of the model with a simple calibration matching the main empirical results of this paper is presented in the Appendix. In this section we provide the basic intuition of the model.

Specifically, we model a dynamic economy in which firms are heterogeneous in two dimensions: productivity and state-connectedness, both of which affect their ability to access external finance. Private firms are operated by skilled entrepreneurs, have higher productivity, and rely on both private investments and bank loans to grow. As they grow

[33]Dobson and Kashyap (2006) (pg 133) quote a Chinese bank manager saying, "If I lend money to an SOE and it defaults, I will not be blamed. But if I make a loan to a privately-owned shoe factory and it defaults, I will be blamed." We note that various forms of subsidies to state-connected firms can also be interpreted as an alternative manifestation of the state guarantees.

in booms, the increased asset base allow them to pledge more to borrow. On the other hand, state-connected firms are neoclassical, employ regular workers and in equilibrium only borrow from banks because they are not constrained by the limited pledgeability. Moreover, the implicit government bail-out of state-connected firms implies differential interest rates the banks rationally charge to SOEs and private firms. We therefore differ from Song et al. (2011) by explicitly modeling recessions and stimulus, and the implicit government bail-out of state-connected 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 that drives growth in normal times slows down and can potentially reverse. We also show that credit expansions amplify this effect. In our model, a credit-supply increase drives more bank capital to be allocated to SOEs and increase their employment, crowding out private firms in the labor market. Our model thus demonstrates how the same friction can produce different outcomes before and after the recession and stimulus-driven credit expansion just as we document empirically, establishing state-connectedness as the plausible mechanism.

6 Conclusions

Governments in emerging economies introduced large stimulus programs in response to the global financial crisis. These programs have been praised by international organizations and economists alike. 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. However, there is scarce direct empirical evidence on the effectiveness of these programs in emerging countries, and especially on their effects on the allocation of resources across firms.

This paper provides micro evidence on credit allocation across firms during the Chinese economic stimulus plan of 2009-2010. In particular, we focus on the credit expansion policies – such as lower required reserve ratios and lower benchmark lending rates for commercial banks – introduced by the Central Bank of China with the objective of increasing credit supply to the real economy. 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. In the empirical analysis, we match 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. Importantly, we document that this is a reversal of the previous trend of factor reallocation from low-productivity state-owned firms to high-productivity private firms that contributed to China's growth up to 2008.

Our findings also illustrate how financial frictions interact with business cycle and credit expansion, leading to potentially unintended consequences of government interventions. In this sense, the results presented in this paper can apply outside the context of China and are informative for other emerging countries that undertook large stimulus programs in response to the Great Recession and whose credit markets are plagued by severe financial frictions.

References

Acharya, 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 (2014). Crony capitalism with chinese characteristics. *University of Chicago, working paper*.

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

Banerjee, A. and K. Munshi (2004). How efficiently is capital allocated? evidence from the knitted garment industry in tirupur. *The Review of Economic Studies 71*(1), 19–42.

Banerjee, A. V. and E. Duflo (2014). Do firms want to borrow more? testing credit constraints using a directed lending program. *Review of Economic Studies 81*(2), 572–607.

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 H. Li (2002). Bank discrimination in transition economies: ideology, information or incentives? *Working Paper*.

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.

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

Caballero, R. J., T. Hoshi, and A. K. Kashyap (2008). Zombie lending and depressed restructuring in japan. *The American Economic Review 98*(5), 1943–1977.

Carvalho, D. (2014). The real effects of government-owned banks: Evidence from an emerging market. *The Journal of Finance 69*(2), 577–609.

Chaney, T., D. Sraer, and D. Thesmar (2012). The collateral channel: How real estate shocks affect corporate investment. *The American Economic Review 102*(6), 2381–2409.

Chang, C., Z. Liu, M. M. Spiegel, and J. Zhang (2017). Reserve requirements and optimal chinese stabilization policy. Federal Reserve Bank of San Francisco.

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. and J. Haltiwanger (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.

Dobson, W. and A. K. Kashyap (2006). The contradiction in china's gradualist banking reforms. *Brookings Papers on Economic Activity 2006*(2), 103–162.

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.

Ho, C.-Y., D. Li, S. Tian, and X. Zhu (2017). Policy distortion in credit market: Evidence from a fiscal stimulus plan. *Working Paper*.

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.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica 82*(2), 463–505.

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 (2005). Do lenders favor politically connected firms? rent provision in an emerging financial market. *The Quarterly Journal of Economics 120*(4), 1371–1411.

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.

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

Li, H., L. Meng, Q. Wang, and L.-A. Zhou (2008). Political connections, financing and firm performance: Evidence from chinese private firms. *Journal of development economics 87*(2), 283–299.

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.

Peek, J. and E. S. Rosengren (2000). Collateral damage: Effects of the japanese bank crisis on real activity in the united states. *American Economic Review*, 30–45.

Peek, J. and E. S. Rosengren (2005). Unnatural selection: Perverse incentives and the misallocation of credit in japan. *The American Economic Review 95*(4), 1144–1166.

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.

Sapienza, P. (2004). The effects of government ownership on bank lending. *Journal of financial economics 72*(2), 357–384.

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

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

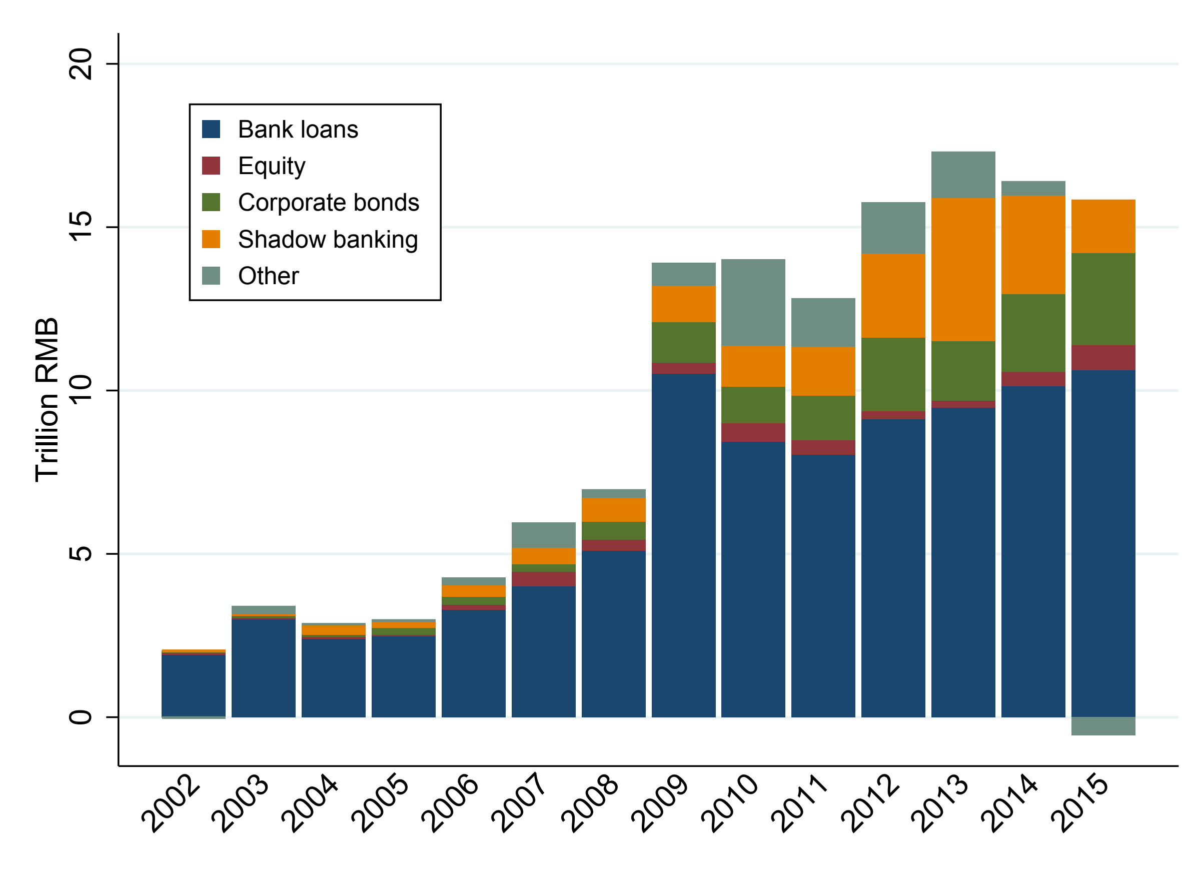
Wang, H., H. Wang, L. Wang, and H. Zhou (2016). Shadow banking: China's dual-track interest rate liberalization.

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

Zingales, L. (2014). *A capitalism for the people: Recapturing the lost genius of American prosperity*. Basic books.

Figures and Tables

Figure 1: Aggregate Financing to the Real Economy



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 2: Structure of China Economic Stimulus Plan

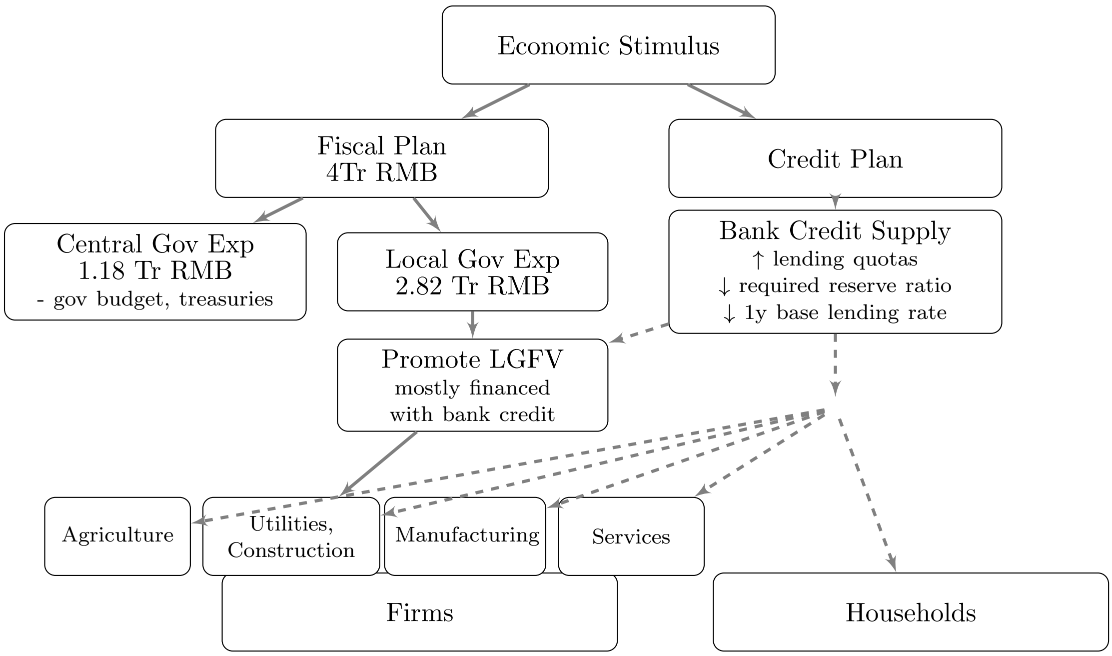
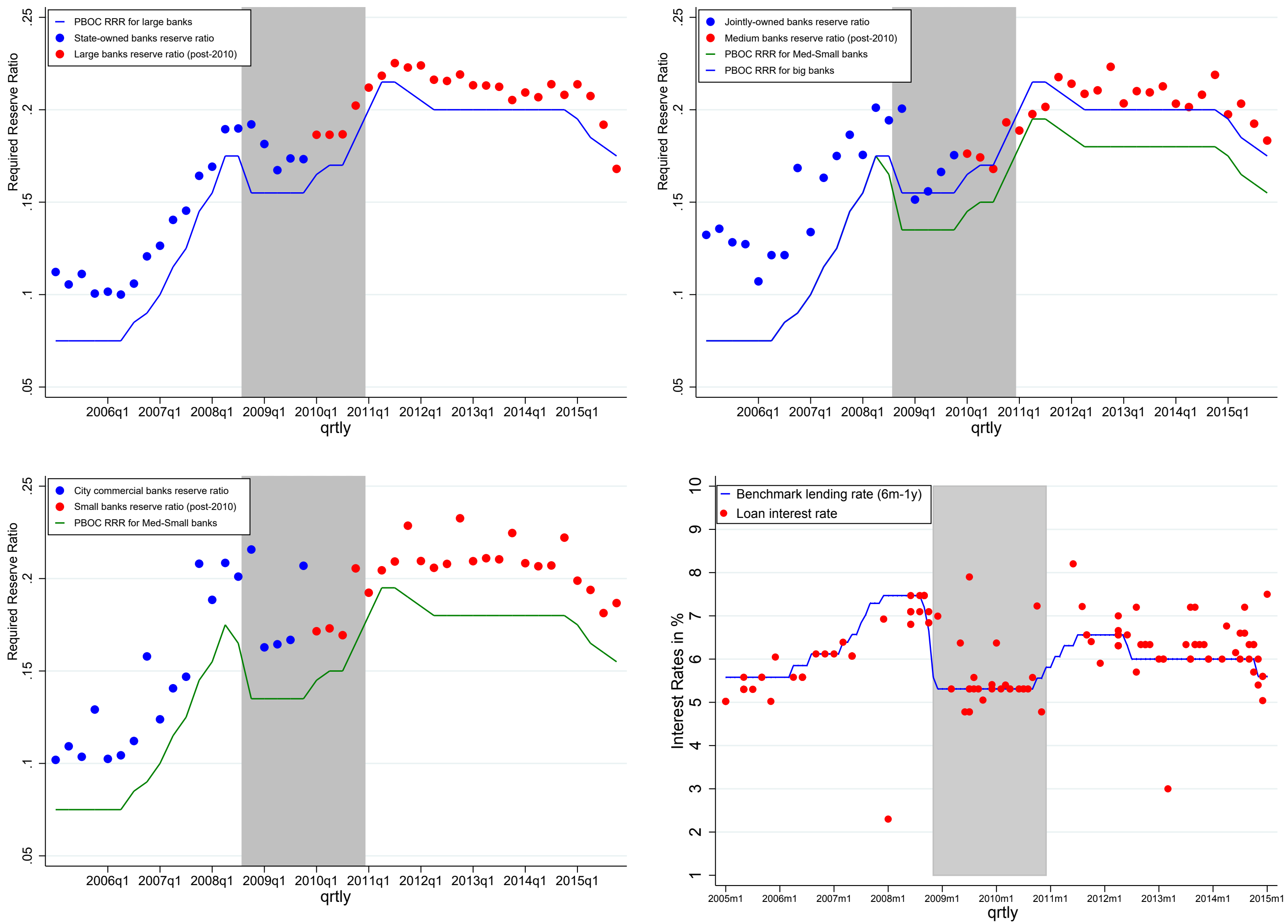


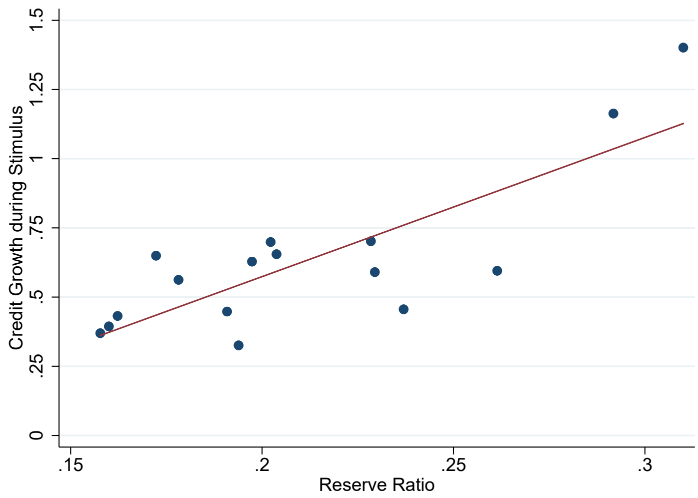
Figure 3: Changes in Banking Regulation during Stimulus Years:

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.

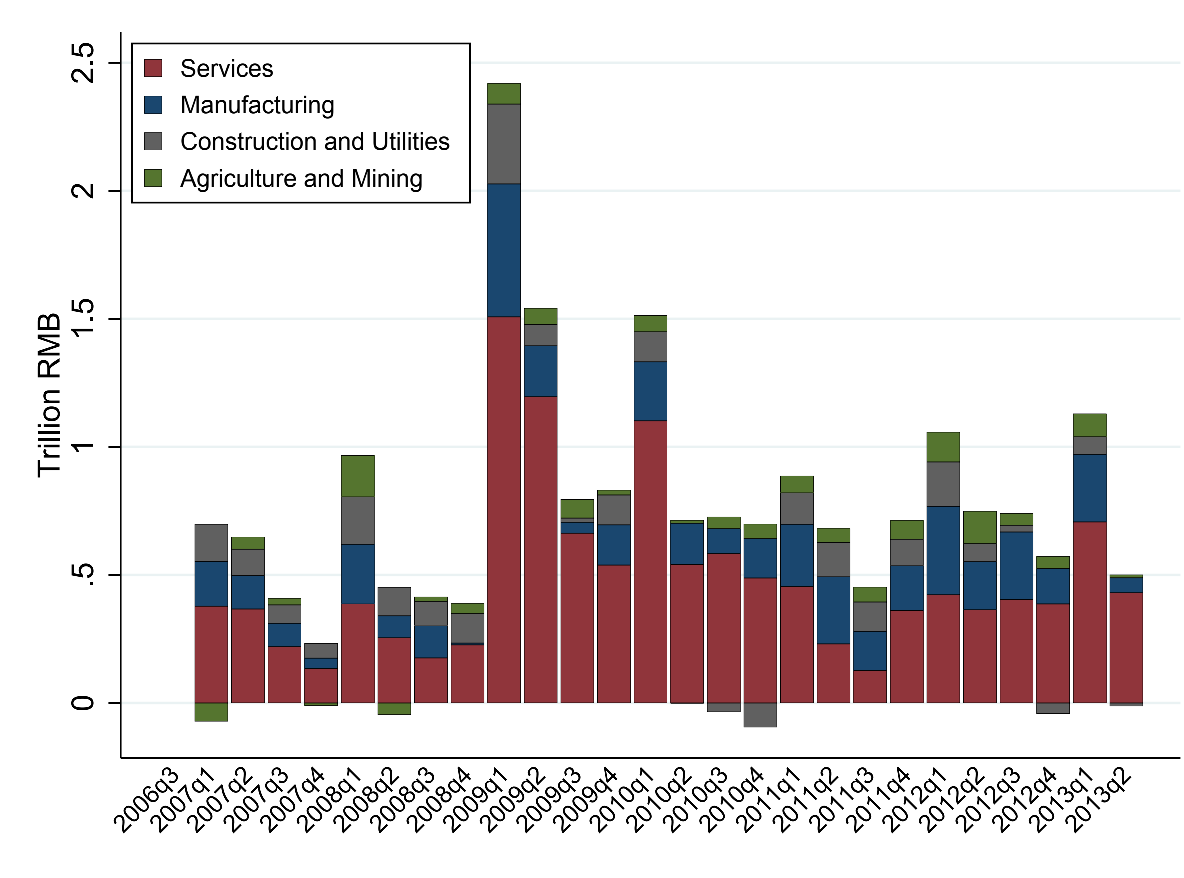
Figure 4: Reserve Ratio and Credit Growth



Notes: Source: Banks' Annual Reports and China Banking Regulatory Commission. Reserve Ratio at bank level refer to year 2007 and it is available from 16 out 19 banks in our sample. Credit growth is computed as the percentage increase in bank lending between the pre-stimulus years (2007 and 2008) and the stimulus years (2009 and 2010).

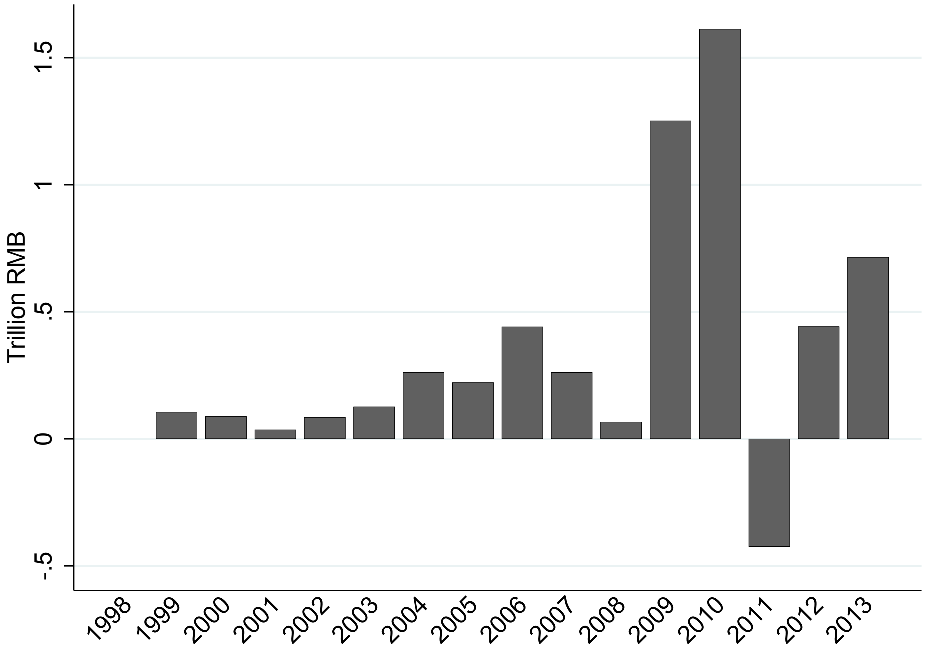
Figure 5: Bank Lending to Firms - by Sector

Quarterly Data, 2007-2013



Notes: Source: China Banking Regulatory Commission. To produce this graph we first sum across firms the monetary value of their outstanding loan balance at the end of each quarter. Then we take a quarter to quarter difference of the sum.

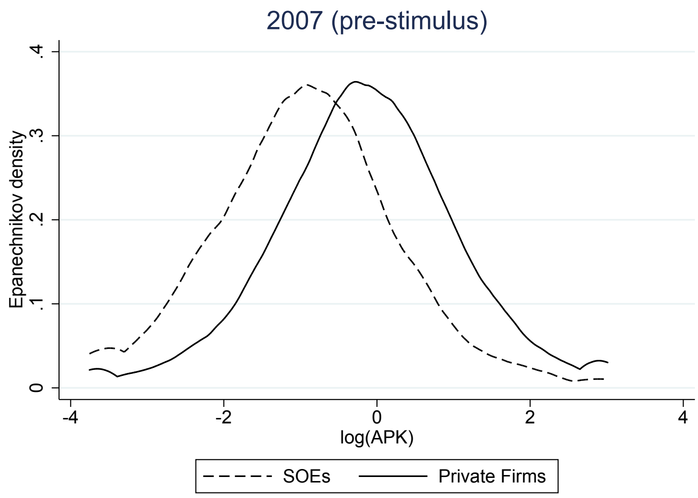
Figure 6: Change in Long-term Liabilities - Manufacturing Sector
Yearly data, 1998-2013



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

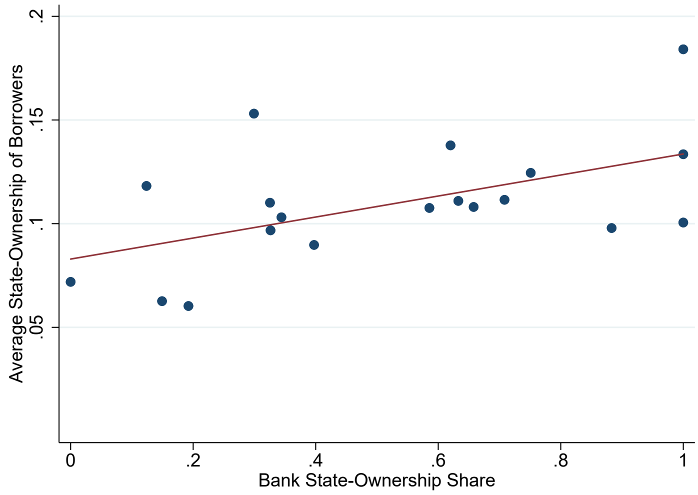
Figure 7: Average Product of Capital

Distribution for Private Firms and SOEs



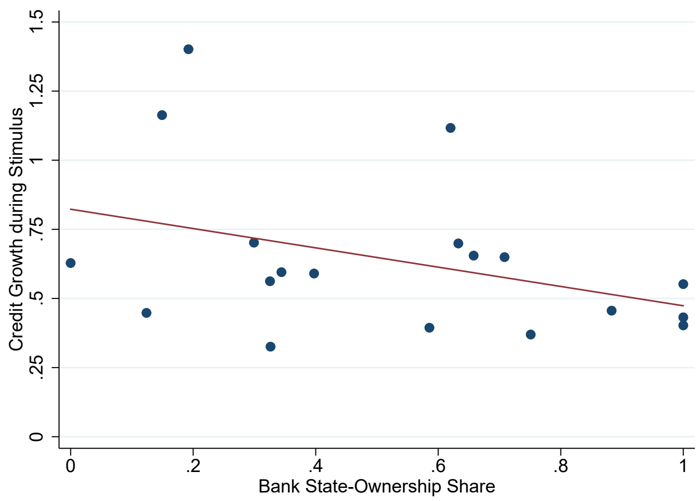
Notes: Source: National Bureau of Statistics, Annual Industrial Survey.

Figure 8: Bank and Firm State-Ownership Connection



Notes: Source: Banks' Annual Reports, China Banking Regulatory Commission and Manufacturing Survey. Bank State-Ownership Share is the sum of the ownership share of financial institutions under the direct control of the central government, funds under the control of local governments, and state-owned firms. Average State-Ownership of Borrowers is the value weighted share of a bank lending portfolio to manufacturing firms allocated to SOEs. Both variables refer to year 2008.

Figure 9: Bank State-Ownership and Credit Growth during Stimulus



Notes: Source: Banks' Annual Reports and China Banking Regulatory Commission. Bank State-Ownership Share is the sum of the ownership share of financial institutions under the direct control of the central government, funds under the control of local governments, and state-owned firms; ownership data refers to year 2008. Credit growth is computed as the percentage increase in bank lending between the pre-stimulus years (2007 and 2008) and the stimulus years (2009 and 2010).

Table 1: Summary Statistics

Variable Name	Mean	Median	St.Dev.	N
Panel A: CBRC loan-level data:				
$loan_{ibt}$ (million RMB)				
all years	163	63	452	177,089
stimulus years	179	68	474	39,007
stimulus years, firm-level	554	156	1791	11,068
$\Delta \log loan_{ibt}$				
all years	0.039	0.000	0.433	177,089
stimulus years	0.033	0.000	0.461	39,007
stimulus years, firm-level ($\Delta \log loan_{it}$)	0.095	0.048	0.442	11,068
Panel B: Annual Survey of Industrial firms:				
number of employees	2,143	702	7,404	11,068
fixed assets (thousand RMB)	731,024	120,931	3,698,495	11,068
sales (thousand RMB)	1,620,140	421,161	6,253,501	11,068
$StateShare$	0.113	0.000	0.290	11,068
age (year)	14	10	14	11,068
exporter dummy	0.444	0.000	0.497	11,068
publicly listed dummy	0.052	0.000	0.223	11,068
Δ log employment	0.027	0.045	0.598	11,068
Δ (fixed assets$_t$ / sales$_{t-1}$)	-0.041	-0.024	0.317	11,068
Panel C: independent variables:				
$\Delta \log L_{b-cj,t}$				
all years	0.132	0.117	0.114	177,089
stimulus years	0.234	0.191	0.127	39,007
$\Delta \widetilde{L_{icjt}}$	0.222	0.204	0.116	11,068

Notes: The table reports summary statistics for the main variables used in the empirical analysis. For a detailed discussion of the data sources see Section 3.

Table 2: Persistence of Bank-Firm Credit Relationships

outcome:	New loan from lender$_{bi,t}$	
sample:	all years	stimulus years
	(1)	(2)
Pre-existing banking relationship	0.949	0.941
	[0.001]***	[0.001]***
Year FE	y	y
Lender FE	y	y
Industry FE	y	y
City FE	y	y
R-squared	0.807	0.789
Observations	882,580	252,167

Notes: The outcome variable is a dummy equal to 1 if firm i takes a new loan from bank b at time t. Each observation in the dataset is a potential bank-firm relationship, i.e. for each firm and year, there is an observation for each potential lender. The independent variable is a dummy equal to 1 if firm i had a pre-existing credit relationship with bank b at time $t-1$. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Bank Credit Supply and Loans

outcome:	$\Delta \log loan_{ibt}$							
sample:	all years: 2006-2013				stimulus years: 2009-2010			
	all firms		multi-lender		all firms		multi-lender	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log L_{b-cj,t}$	0.145	0.146	0.130	0.163	0.152	0.152	0.154	0.176
	[0.045]***	[0.046]***	[0.049]**	[0.058]**	[0.065]**	[0.066]**	[0.075]*	[0.089]*
Year FE	y	y	y	-	y	y	y	-
Industry FE	y	y	y	y	y	y	y	y
City FE	y	y	y	y	y	y	y	y
Firm Characteristics	-	y	y	-	-	y	y	-
Firm × Year FE	-	-	-	y	-	-	-	y
R-squared	0.012	0.012	0.012	0.341	0.026	0.026	0.030	0.350
Observations	177,089	177,089	143,525	143,525	39,004	39,004	31,225	31,225

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. Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Standard errors are clustered at main lender level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The Effect of Bank Credit Supply on Firm-level outcomes

Loans, Investment and Employment. Stimulus Years (2009-2010)

outcome:	$\Delta \log loan_{it}$		$\Delta(\frac{K}{PY})_{it}$		$\Delta \log L_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \widetilde{L_{icjt}}$	1.010	1.003	0.108	0.099	0.346	0.297
	[0.086]***	[0.086]***	[0.049]**	[0.050]**	[0.102]***	[0.100]***
Year FE	y	y	y	y	y	y
Industry FE	y	y	y	y	y	y
City FE	y	y	y	y	y	y
Firm Characteristics	-	y	-	y	-	y
R-squared	0.092	0.094	0.222	0.224	0.227	0.247
Observations	11,068	11,068	11,068	11,068	11,068	11,068

Notes: The unit of observation is a firm. The dependent variables are: the yearly change in the log of total outstanding bank loan balance in columns (1) & (2), the yearly change in tangible capital as a share of firm value of production in columns (3) & (4), the yearly change in the log of average number of workers in columns (5) & (6). Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Standard errors are clustered at city level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Heterogeneous Effects of Bank Credit Supply
Stimulus Years (2009-2010)

outcome:	$\Delta \log loan_{it}$				
sample:	all firms		$StateShare_{i,t=0}$		all firms
			$= 0$	> 0	
	(1)	(2)	(3)	(4)	(5)
$\Delta\widetilde{L_{icjt}}$	0.993	0.985	0.961	1.245	0.974
	[0.088]***	[0.089]***	[0.092]***	[0.257]***	[0.085]***
$\log APK_{i,t=0}$	0.047	0.047	0.052	-0.002	0.034
	[0.008]***	[0.008]***	[0.008]***	[0.021]	[0.005]***
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0}$	-0.059	-0.060	-0.059	0.037	
	[0.027]**	[0.027]**	[0.028]**	[0.079]	
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0}$					0.376
					[0.119]***
$StateShare_{i,t=0}$					-0.074
					[0.027]***
Year FE	y	y	y	y	y
Industry FE	y	y	y	y	y
City FE	y	y	y	y	y
Firm Characteristics	-	y	y	y	y
R-squared	0.097	0.099	0.101	0.220	0.100
Observations	11,068	11,068	9,254	1,787	11,068

Notes: The unit of observation is a firm. The dependent variable is the yearly change in the log of total outstanding bank loan balance. Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Standard errors are clustered at city level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Dynamic of Credit Allocation Across Firms:
All Years (2006-2013)

outcome:	$\Delta \log loan_{it}$					
sample:	all firms			$StateShare_{i,t=0}$		all firms
				$= 0$	> 0	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0}$	0.098	0.093	0.117	0.109	-0.022	
	[0.045]**	[0.045]**	[0.050]**	[0.053]**	[0.118]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(stimulus)$	-0.156	-0.152	-0.152	-0.166	0.041	
	[0.047]***	[0.047]***	[0.060]**	[0.057]***	[0.142]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(post)$	-0.067	-0.064	-0.020	-0.067	0.195	
	[0.060]	[0.061]	[0.067]	[0.070]	[0.171]	
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0}$						-0.465
						[0.211]**
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(stimulus)$						0.855
						[0.240]***
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(post)$						0.672
						[0.292]**
$\Delta\widetilde{L_{icjt}}$	1.308	1.296	1.432	1.308	1.166	1.311
	[0.098]***	[0.099]***	[0.122]***	[0.101]***	[0.351]***	[0.096]***
$\Delta\widetilde{L_{icjt}} \times I(stimulus)$	-0.325	-0.319	-0.338	-0.365	0.090	-0.348
	[0.133]**	[0.135]**	[0.154]**	[0.142]**	[0.380]	[0.134]***
$\Delta\widetilde{L_{icjt}} \times I(post)$	0.210	0.208	-0.249	0.137	1.034	0.182
	[0.149]	[0.149]	[0.210]	[0.155]	[0.488]**	[0.147]
$StateShare_{i,t=0}$						0.078
						[0.040]*
$StateShare_{i,t=0} \times I(stimulus)$						-0.154
						[0.049]***
$StateShare_{i,t=0} \times I(post)$						-0.079
						[0.045]*
$\log APK_{i,t=0}$	0.013	0.014	-0.001	0.007	0.046	0.029
	[0.009]	[0.009]	[0.012]	[0.010]	[0.023]**	[0.003]***
$\log APK_{i,t=0} \times I(stimulus)$	0.031	0.030	0.031	0.039	-0.036	
	[0.011]***	[0.011]***	[0.014]**	[0.013]***	[0.031]	
$\log APK_{i,t=0} \times I(post)$	0.011	0.010	0.006	0.013	-0.027	
	[0.010]	[0.010]	[0.012]	[0.011]	[0.026]	
Year FE	y	y	y	y	y	y
Industry FE	y	y	y	y	y	y
City FE	y	y	y	y	y	y
Firm Characteristics	-	y	y	y	y	y
Firm FE	-	-	y	-	-	-
R-squared	0.068	0.069	0.344	0.070	0.123	0.070
Observations	46,583	46,583	42,938	39,135	7,440	46,583

Notes: The unit of observation is a firm. The dependent variable is the yearly change in the log of total outstanding bank loan balance. $I(stimulus)$ is a dummy equal to 1 for the years 2009 and 2010. $I(post)$ is a dummy equal to 1 for the years 2011 to 2013. Data covers the period 2006 to 2013. Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Standard errors are clustered at city level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Dynamic of Credit Allocation Across Firms: Real Effects and Loan Performance. All Years (2006-2013)

PANEL A, outcome:	$\Delta(\frac{K}{PY})_{it}$					
sample:	all firms			$StateShare_{i,t=0}$		all firms
				$= 0$	> 0	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0}$	0.111 [0.082]	0.100 [0.082]	0.026 [0.106]	0.037 [0.092]	0.161 [0.094]*	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(stimulus)$	-0.355 [0.136]***	-0.344 [0.136]**	-0.289 [0.159]*	-0.162 [0.140]	-0.122 [0.131]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(post)$	-0.063 [0.124]	-0.055 [0.124]	0.276 [0.160]*	-0.003 [0.125]	-0.201 [0.151]	
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0}$						-0.013 [0.173]
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(stimulus)$						0.367 [0.219]*
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(post)$						0.072 [0.231]
Observations	46,565	46,565	42,918	39,129	7,428	46,565
R-squared	0.083	0.084	0.257	0.085	0.165	0.154
PANEL B, outcome:	$\Delta \log L_{it}$					
sample:	all firms			$StateShare_{i,t=0}$		all firms
				$= 0$	> 0	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0}$	0.009 [0.046]	-0.071 [0.050]	-0.062 [0.043]	-0.077 [0.053]	-0.166 [0.124]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(stimulus)$	-0.023 [0.093]	0.065 [0.095]	0.062 [0.077]	0.124 [0.102]	0.089 [0.167]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(post)$	0.070 [0.069]	0.152 [0.066]**	0.135 [0.063]**	0.167 [0.071]**	0.257 [0.240]	
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0}$						-0.034 [0.155]
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(stimulus)$						0.732 [0.312]**
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(post)$						-0.165 [0.386]
Observations	46,583	46,583	42,938	39,135	7,440	46,583
R-squared	0.031	0.120	0.458	0.126	0.157	0.120
PANEL C, outcome:	NPL_{it}					
sample:	all firms			$StateShare_{i,t=0}$		all firms
				$= 0$	> 0	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0}$	-0.151 [0.039]***	-0.147 [0.039]***	-0.110 [0.045]**	-0.135 [0.041]***	-0.119 [0.107]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(stimulus)$	0.173 [0.048]***	0.168 [0.048]***	0.146 [0.057]**	0.157 [0.051]***	0.100 [0.121]	
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0} \times I(post)$	0.156 [0.050]***	0.155 [0.050]***	0.156 [0.069]**	0.146 [0.053]***	0.096 [0.165]	
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0}$						0.419 [0.175]**
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(stimulus)$						-0.489 [0.199]**
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0} \times I(post)$						-0.433 [0.249]*
Observations	39,226	39,226	34,926	33,456	5,753	39,226
R-squared	0.106	0.113	0.422	0.105	0.207	0.112
All panels:						
Year Industry City FE	y	y	y	y	y	y
Firm Characteristics	-	y	y	y	y	y
Firm FE	-	-	y	-	-	-

Notes: The unit of observation is a firm. NPL_{it} is the value-weighted share of loans originated in year t to firm i which are eventually non-performing (90 days or more delinquent). $I(stimulus)$ is a dummy equal to 1 for the years 2009 and 2010. $I(post)$ is a dummy equal to 1 for the years 2011 to 2013. Data covers the period 2006 to 2013. Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Main effects of equation 5 included in all specifications but not reported. Standard errors are clustered at city level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix A: A Dynamic Model of Transitional Economy

This section develops a dynamic model to illustrates how financial frictions affect credit allocation across firms and establish state-connectedness as a plausible channel for rationalizing our empirical findings. 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. It also deepens our understanding on how financial frictions exhibit differential impacts across business and credit cycles.

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 shortly, 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 S firms or P firms, and get paid the equilibrium wage when the firm is successful, which they consume in each period.[34] We set N_t to be a constant to focus on the labor share dynamics and illustrate key mechanisms.

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 inter-temporal elasticity of substitution in consumption c that ensures private investment (discussed later) to be non-decreasing in the rate of return, t marks the period in which an entrepreneur is born. We similarly normalize $M_t = 1$. In the first period, young entrepreneurs each starts a P firm (with the help from successful old entrepreneurs from the previous period), makes operation decisions, obtains a fraction 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

[34]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".

R_S in the next period, or a private fund that invests in a diversified portfolio of private enterprises that operate the next period.[35] 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.[36] 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, 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. Second, when 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.[37] $\delta = \frac{\mu}{\mu+(1-\mu)b}$ captures how much S firms are differentially favored in terms of interest rates or cost of capital (the *interest rate friction*).

The differential pledgeability constraints and interest rates can be thought as reflecting several real world frictions commonly observed in emerging economies transitioning to market-based systems but where state influence still lingers (Shleifer and Vishny 1994; Wang et al. 2016), and are consistent with extant theory and empirical studies on China (Song et al. (2011), Chang et al. (2017), and Ho et al. (2017)). For example, loan officers prefer to lend to State-connected firms or SOEs for several reasons: (1) the government more likely bails them out which prevents loan defaults; (2) SOEs are typically larger and perceived to be safer, which enables bankers to complete lending quota or satisfies their empire-building motives with less effort; (3) bankers have less screening cost and responsibility when lending to SOEs, especially during the stimulus, since they are less to blame in the event of default or non-performance. These are issues considered in Ho et al. (2017) as well.

Both these frictions affect the speed of growth of P firms relative to S firms, and 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 are complements and together may further restrict P firms' growth. Both frictions are thus realistic and in combination reflect differential access to credit by S and P firms. That said, we have assumed S firms's productivity disadvantage and financing advantage are perfectly correlated for simplicity.

[35] 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).

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

[37] Implicit bailout is also the driver in Chang 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.

In reality the two are imperfectly correlated.

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 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.

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

Dynamic Equilibrium

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

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

First-order conditions pin down the equilibrium wage $w = (1-\alpha)\left(\frac{\alpha}{R_S}\right)^{\frac{\alpha}{1-\alpha}} A$

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

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

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

If a P firm is successful, the young entrepreneur running it gets paid $\phi[k_P^{\alpha}(\chi An_P)^{1-\alpha} - R_P l_P - wn_P]$. Thus young and old entrepreneurs would take the same decision regarding borrowing and labor employment, fixing private capital s_P.

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

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

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

$$n_P = \chi^{\frac{1-\alpha}{\alpha}}\left(\frac{R_S}{\alpha}\right)^{\frac{1}{1-\alpha}}\frac{k_P}{A} \quad \text{and} \quad \pi(k_P) = \chi^{\frac{1-\alpha}{\alpha}} R_S k_P := \rho k_P.$$

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:

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

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 $\delta\chi^{\frac{1-\alpha}{\alpha}} < 1$, especially during recessions, and P firms stop borrowing. 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:

$$\underbrace{Q_t}_{\text{Credit Supply}} = \underbrace{l_{S_t} + l_{P_t}}_{\text{Credit Supply}} = \underbrace{k_{P,t} + k_{S,t} - s_{P,t}}_{\text{Credit Demand}} \tag{6}$$

$$N_t = n_{P,t} + n_{S,t} = \frac{\chi^{\frac{1-\alpha}{\alpha}}k_{P,t} + k_{S,t}}{A_t}\left(\frac{R_{S,t}}{\alpha}\right)^{\frac{1}{1-\alpha}} \tag{7}$$

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

$$1+\gamma_t = \frac{k_{P,t}}{k_{P,t-1}} = \frac{\psi_t}{(1-\eta B_t)\rho_t\mu_t}\frac{s^*_{P,t}}{k_{P,t-1}} = \phi\frac{\mu_{t-1}\rho_{t-1}}{\mu_t\rho_t}\tilde{\psi}_t\left(1+\beta^{-\theta}((1-\phi)\psi_t)^{1-\theta}\right)^{-1} \tag{8}$$

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. Higher private capital and lower financial frictions 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.

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 (8) 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.

Because credit supply is rationed – which befits China's case – any increase in Q is allocated and invested, which is consistent with our finding that increases in credit supply lead to greater average borrowing and investment, as seen in Table 4. Had we modeled unemployment explicitly, the increase in Q would have led to lower interest rates and pushed up equilibrium wage, which would increase average employment, again consistent with our empirical findings in Table 4.

More importantly, we note that $\frac{\partial(1+\gamma_t)}{\partial Q} < 0$, indicating that the allocation disproportionately favored SOEs. It may seem counter-intuitive that a relaxation of financial constraint (increasing credit supply) does not benefit the more constrained P firms relatively more. To understand this, note that an increase in Q will cause $R_{S,t}$ to fall, then ψ_t (which reflects private capital productivity) decreases through a general equilibrium effect, which leads to a decrease in future private investment s.[38] 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.[39] 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.

Therefore, both credit expansion or decline in economic environment in the presence of credit allocation friction slow down P firms' growth. 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).

These results rationalize what we find empirically about credit allocation and firm outcomes in Tables 5-8. In particular, credit increase during stimulus years had a larger impact on firm borrowing and employment for state-owned firms than for private firms.

Finally, we illustrate these predictions of the model in terms of credit share of S firms in Figure 10 (capital and labor shares have similar patterns). Panel (a) 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). Prior to the recession and credit expansion, the pattern is consistent with the mechanism for China's growth in

[38] 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 disproportionately 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.

[39] 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.

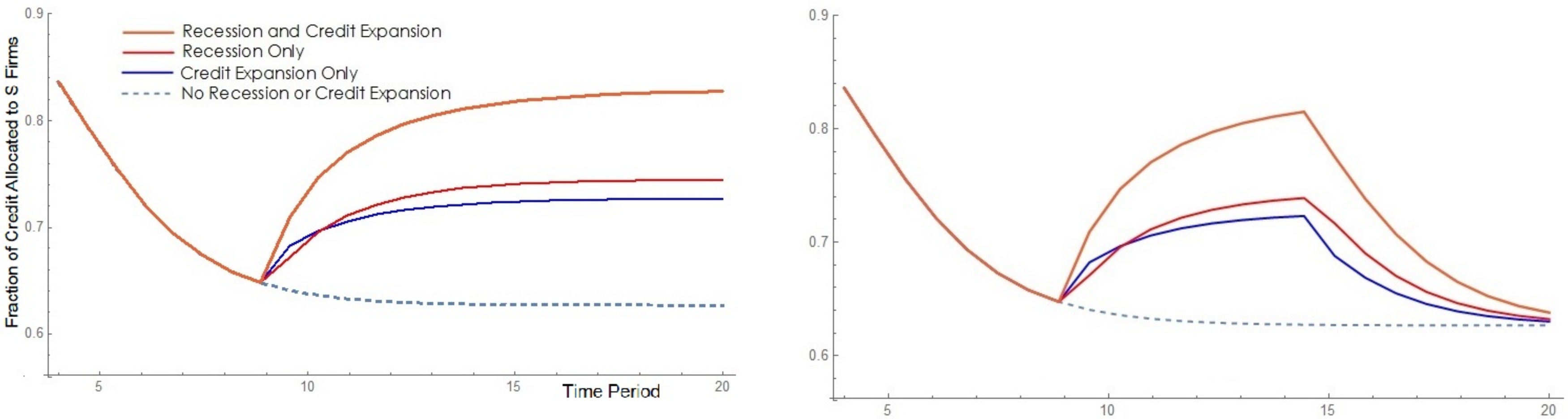
Song et al. (2011). The Panel also demonstrates that both recession and credit expansion can slow down or reverse the efficient reallocation, and credit expansion during recession exacerbates the reversal, corroborating our empirical findings in Tables 6-7. Panel (b) shows the case in which the economy 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 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 is consistent with Tables 6-7 discussed earlier, and can have significant cumulative impact on real outputs and economic growth.

Figure 10: 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 $\mu = 0.91$).

Appendix B : Additional Tables

Table A1: The Effect of Bank Credit Supply on Firm-level outcomes

Additional Evidence: Loan Maturity. Stimulus Years (2009-2010)

outcome:	$maturity_{it}$	
	(1)	(2)
$\Delta \log L_{b-cj,t}$	6.707	6.950
	[2.334]**	[2.412]***
Year FE	y	y
Industry FE	y	y
City FE	y	y
Firm Characteristics	-	y
R-squared	0.118	0.119
Observations	176,575	176,575

Notes: The unit of observation is a bank-firm credit relationship. The outcome *maturity* is the value weighted average maturity of new loans issued to firm i in year t (in months). Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Standard errors are clustered at main lender level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Heterogeneous Effects of Bank Credit Supply
Robustness to Excluding Input Suppliers to Construction and Utilities

outcome:	$\Delta \log loan_{it}$				
sample:	all firms		$StateShare_{i,t=0}$		all firms
			$= 0$	> 0	
	(1)	(2)	(3)	(4)	(5)
$\Delta\widetilde{L_{icjt}}$	0.939	0.930	0.910	1.188	0.921
	[0.090]***	[0.091]***	[0.094]***	[0.261]***	[0.087]***
$\log APK_{i,t=0}$	0.049	0.049	0.053	0.006	0.034
	[0.008]***	[0.008]***	[0.009]***	[0.023]	[0.006]***
$\Delta\widetilde{L_{icjt}} \times \log APK_{i,t=0}$	-0.067	-0.068	-0.067	0.026	
	[0.028]**	[0.028]**	[0.030]**	[0.084]	
$\Delta\widetilde{L_{icjt}} \times StateShare_{i,t=0}$					0.420
					[0.128]***
$StateShare_{i,t=0}$					-0.078
					[0.028]***
Observations	10,064	10,064	8,509	1,528	10,064
R-squared	0.100	0.102	0.105	0.230	0.103
Year FE	y	y	y	y	y
Industry FE	y	y	y	y	y
City FE	y	y	y	y	y
Firm Characteristics	-	y	y	y	y

Notes: The unit of observation is a firm. The dependent variable is the yearly change in the log of total outstanding bank loan balance. Firm characteristics are: 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), firm age, and a dummy equal to 1 if the firm is publicly traded. Firm characteristics are observed in year $t-1$. Input suppliers to Construction and Utilities are firms operating in the following sectors: basic metals, non-metallic mineral products, mining and quarrying. Standard errors are clustered at city level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Ex-Post Loan Performance and Firm Characteristics

outcome:	NPL_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
$StateShare$	0.006					
	[0.003]*					
$\log APK$		-0.004				
		[0.001]***				
log Sales			-0.007			
			[0.001]***			
Export				-0.005		
				[0.001]***		
Age					0.000	
					[0.000]	
I(public)						-0.005
						[0.002]**
Observations	39,226	39,226	39,214	39,226	39,202	39,226
R-squared	0.065	0.067	0.070	0.066	0.065	0.065

Notes: The table reports the estimated coefficients of a set of regressions where the outcome variable is NPL_{it} and the explanatory variables are different firm characteristics. NPL_{it} is the value-weighted share of loans originated in year t to firm i which are eventually non-performing (90 days or more delinquent). The unit of observation is a firm. Standard errors are clustered at city level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.