

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 find that the stimulus-driven credit expansion disproportionately favored state-owned firms and firms with lower marginal product of capital, reversing the process of capital reallocation towards private firms that characterized China high growth before 2008. We rationalize these findings in a dynamic model with financial frictions. In normal times, growth is driven by gradual reallocation of resources from low to high productivity firms. Recessions can slow down or even reverse this process due to implicit government bailout favoring state-connected firms. Credit expansion further amplifies this effect.

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

This paper studies the financial and real effects of a major credit expansion program in China. 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.¹ 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 entail a set of credit expansion policies – including lower bank reserve requirements and lower benchmark lending rates – aimed at increase lending to the real economy by Chinese banks. As shown in Figure 2, 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, we provide micro-evidence on the impact of the Chinese credit stimulus plan on firm borrowing and real outcomes. Second, we study the allocation of new credit across firms. In particular, we investigate how new credit was allocated across firms with different initial connections to the government. To

¹The 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 end, we use confidential loan-level data from the 19 largest Chinese banks. This data is collected by the China Banking Regulatory Commission, and covers 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. This allows us to study credit allocation across firms with different initial characteristics – such as state-ownership and productivity – during the stimulus years. 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.

The main identification challenge we face is to isolate changes in firm borrowing that are solely driven by credit supply forces and not by credit demand or investment opportunities. To this end, we use loan-level data to construct a measure of firm exposure to the credit supply generated by the stimulus plan. Our methodology exploits two sources of variation: first, banks increased their aggregate lending differently in response to the stimulus policies; second, 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 as the change in aggregate lending to other borrowers by a firm pre-stimulus lenders.

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. Our merged dataset then allows us to study the effect of credit supply changes on firm borrowing and real outcomes, as well as the heterogeneous effects across firms with different initial characteristics. In what follows we describe our main findings.

First, we document that our measure of credit supply changes effectively explains

variation in firm borrowing. We find that a one percent increase in credit supply from pre-existing lenders translates into an increase in firm borrowing of similar magnitude. We also document that credit supply changes during the stimulus years had significant real effects on investment and employment. In particular, our estimated elasticities indicate that firms with a 1 percent larger exposure to increases in credit supply experienced a 0.23 percent larger increase in investment, and a 0.33 larger increase in employment during the stimulus years. These results indicate that the Chinese credit expansion in response to the global financial crisis had real effects on investment and employment.

Next, we turn to the heterogeneous effects of the stimulus and credit expansion across firms. In particular, we find that the effect of increases in credit supply on firm borrowing was 36% larger for state-owned firms relative to private firms during the stimulus years. We also show that, over the same period, the effect of credit supply on firm borrowing was larger for firms with lower pre-stimulus marginal productivity of capital, which is consistent with existing evidence that Chinese state-owned firms are, on average, less productive than private firms.² These results are also consistent with the argument that one of the effects of the Chinese fiscal stimulus program has been an increase in the misallocation of resources across firms in the Chinese economy (Bai, Hsieh, and Song (2016)). In terms of real effects, we show that, relative to private firms, state-owned firms had a four times larger elasticity of employment to increases in bank credit supply during the stimulus years. Taken together, these results suggest that the larger allocation of credit towards state-owned firms observed during the stimulus years might have attenuated the effect of the global financial crisis on unemployment potentially at the expense of facilitating productive investment and long-run growth.

Finally, we study how credit allocation across firms in China has changed over time. For this purpose, we extend our identification strategy to both the pre-stimulus and the

²Several 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 marginal product of capital between SOE and non-SOE has been closing in the years between 1999 and 2007, but nonetheless find that, in 2007, “capital productivity among state-owned firms and privatized firms remained about 40 percent lower (compared to private firms).”

post-stimulus periods. Two important findings emerge. First, we find that, in the pre-stimulus period, the effect of changes in credit supply on firm borrowing were larger for private firms and for firms with higher initial marginal productivity of capital. 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 by several scholars an important driver of its growth performance in that period. Second, the change in the trend of credit allocation between private and state-owned firms did not reverse back at the end of the stimulus years, indicating potential persistent effects of the stimulus policies.

To rationalize these findings and further understand the dynamics of credit allocation, we build on Song et al. (2011) to model a dynamic economy in which firms are heterogeneous in two dimensions: productivity and state-connectedness, both of which affect their ability to access external finance. Private firms are operated by skilled entrepreneurs, have higher productivity, and rely on both private investments and bank loans to grow. On the other hand, state-connected firms are neoclassical, employ regular workers and in equilibrium only borrow from banks. We augment the original framework 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 is 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 the growth experience of China in the early 2000s. For example, Song et al. (2011) propose a model where factor reallocation from less productive but financially integrated firms to more productive but credit-rationed firms can rationalize both China's fast economic growth and its large net foreign surplus despite a high rate of return on domestic investment. Consistent with this argument, 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. Consistently with previous literature, we provide evidence of a gradual reallocation of capital from low to high productivity firms in the years up to 2008. Second, we document that this trend has reversed with the introduction of the stimulus plan.³

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

³To be clear, a number of papers such as Firth, Lin, Liu, and Wong (2009) and Boyreau-Debray and Wei (2005) have shown that there is misallocation in China favoring SOEs or certain strategic regions and sectors. What is new is the dynamics of reallocation driven by the recession and the stimulus package.

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. This result applies whenever state-connected firms have lower marginal productivity of capital, a stylized fact observed also outside of China.⁴

Additionally – and due to the same frictions – credit booms can tilt the allocation of resources towards less productive firms, thus increasing misallocation. In this sense, our paper is related to Gopinath et al. (2015), that show that, following the adoption of the euro, countries in the South of Europe, which are characterized by less developed financial markets, experienced both an increase in capital inflows and an increase in misallocation of resources across manufacturing firms. Our paper shows that this effect is amplified when credit increases happen during bad times, as in the case of the Chinese stimulus plan.

Finally, our paper is also related to a new wave of research that studies the drivers and consequences of China’s credit boom, and in particular the large increase in debt of Chinese local governments and the rise of shadow banking. The 2008 stimulus plan encouraged the creation of LGFVs, and several recent papers have analyzed the unintended consequences of this financial liberalization. Huang, Pagano, and Panizza (2016) exploit variation in debt issuance across Chinese cities to show that public debt issuance by local governments crowded out private investment by Chinese firms. Bai 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.⁵

Closely linked to China’s recent credit boom is the rise of shadow banking. Hachem and Song (2016) propose a theoretical mechanism whereby stricter liquidity regulation

⁴Barlevy (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.

⁵Other 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).

in the presence of asymmetric bank competition can fuel shadow banking activities and credit growth similar to the one observed in China.⁶ Through an alternative mechanism of debt rollover, Chen, He, and Liu (2017) attribute the unprecedented rapid growth of shadow banking activities in China after 2012 as one of the unintended consequences of the massive fiscal stimulus plan.⁷

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 the local government. 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. To the best of our knowledge, this is the first paper to document with micro data matching lending activity with firm-level outcomes the widespread impact of the stimulus-driven credit expansion on credit allocation and its real effects in China.

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.⁸

⁶Higher loan-to-deposit ratio requirement introduced by the Chinese government push small banks to offer off-balance-sheet wealth management products as a form of regulatory arbitrage. Large banks respond by tightening liquidity in the inter-bank market and lending more to non-financial firms.

⁷Similarly, Archarya, Qian, and Yang (2016) analyze a proprietary panel data on bank-issued wealth management products and argue that the stimulus plan triggered shadow banking and increased fragility in the banking system. However, Wang, Wang, Wang, and Zhou (2016) contend that shadow banking as China’s dual-track interest rate liberalization can lead to efficiency gain.

⁸See, 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 the literatures 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)).

2 Background and Stylized Facts

2.1 China Economic Stimulus Plan

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

The fiscal part of 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 – around two-thirds of the planned investments – were expected to be financed by local governments. At the beginning of 2009, to help local governments access external financing, the central government facilitated and actively encouraged the establishment of LGFVs, off-balance sheet companies set up by local governments to finance mostly investments in public infrastructure and affordable housing projects.⁹

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.¹⁰

⁹Bai et al. (2016) describe LGFVs in details: these companies are the reincarnation of the trust and investment companies of the 1990s, which helped local governments raise funds from both domestic and overseas investors. LGFVs existed before 2009 but their activities were heavily restricted for a prolonged period of time. They are typically endowed with government resources. For example, the authors note that after 2010 when LGFV borrowing requirements were tightened, LGFVs heavily utilized government land as collateral to obtain loans from banks and trusts, and increasingly financed private commercial projects after 2010.

¹⁰Credit 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

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.¹¹ Second, the PBoC reduced the base one-year lending rate from 7.47% to 5.31%.¹²

One of reasons behind the changes in banking regulation was to meet LGFVs’ borrowing needs. Chen et al. (2017) and Bai et al. (2016) estimate that the fiscal investment target not funded by the central government were largely financed by LGFVs and 90% of the increase in local government debts during the stimulus period were in the form of bank loans. However, it should be emphasized that the credit expansion had a broader impact on the Chinese economy beyond supporting LGFVs, whose investment are primarily concentrated in the construction and utility sectors. We show direct evidence of this in section 2.2.3 starting from loan-level data.¹³ In what follows we present a set of stylized facts using both aggregate and micro data consistent with the above description of the stimulus plan.

while meeting this requirement. Reserve requirement ratio and interest rate regulations were also limiting banks’ lending capacities.

¹¹Large 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.

¹²Banks 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.

¹³At 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 non-residential non-LGFV sector received 1 trillion, and the residential sector received 1.4 trillion.

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 2 shows the aggregate credit flow to the real economy according to official data of 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 covers the years between 2002 and 2015 and it is 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.¹⁴ There are two main stylized facts that emerge from Figure 2. 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. The second stylized fact is that 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 2 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

¹⁴The 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.

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 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.

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.¹⁵ 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 2. Our micro-data comes from two sources: the Chinese Banking Regulatory Commission and the Annual Survey of Industrial Firms. Both datasets are

¹⁵The loan-level data from the CBRC used in the empirical analysis does not report information on interest rates.

described in detail in section 3. In this section our objective is twofold. First, to document that the micro data used in the empirical analysis captures the same trends observed in aggregate data. Second, to provide new stylized facts on the allocation of bank credit across sectors during the stimulus years of 2009 and 2010.

We start from the Chinese Banking Regulatory Commission loan-level dataset. Figure 4 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.¹⁶

The loan-level data from the CBRC reports the sector of operation of the borrower. This allows us to separate the increase in bank lending observed in the stimulus years between different sectors. We categorize borrowers in four main sectors: agriculture and mining, manufacturing, construction and utilities, and services. Figure 4 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, we document that the largest increases in bank lending occurred in manufacturing and services. This indicates that the credit stimulus plan 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. We document that firms covered in this survey displayed a sharp increase in long-term liabilities during the years of the stimulus plan. Figure 5 shows

¹⁶The annual increase in outstanding bank loans to firms in the CBRC data is 1.9 Tr RMB for 2007 and 2.2 Tr RMB for 2008. Comparing Figure 4 with Figure 2 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 2 reports aggregate bank lending to both firms and households, while the CBRC data reported in Figure 4 only captures lending to firms.

the yearly change in aggregate long-term liabilities of manufacturing firms covered in the survey. As shown, there is a sharp and positive increase in long-term liabilities 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 of the China's National Bureau of Statistics. In what follows we describe in more details each of these datasets.

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 Annual Survey of Industrial Firms covers firms operating in the manufacturing sector from year 1998 to 2013. All firms with annual sales above a given monetary threshold are surveyed, making this effectively a census of medium to large size Chinese firms. Until 2010, this threshold was set at 5 million RMB (730,000 USD), and then raised to 20 million RMB (3 million USD) from 2011 onward.¹⁷ The main firm-level variables of interest in our empirical analysis are number of employees, total fixed assets, and

¹⁷Until 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.

ownership status. We use annual changes in total fixed assets as a proxy for investment. Another key variable in our analysis is state ownership. The Annual Survey of Industrial Firms reports the legal registration status of each firm, 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.

Table 1, Panel B reports the main summary statistics for the sample of firms covered in the Annual Industrial Survey that we can match with the CBRC loan-level data. Notice that these summary statistics refer to the stimulus years 2009 and 2010. As shown, Chinese firms with access to bank finance are relatively large. The average number of employees is 2,144 and the average annual sales are 1.6 Bn RMB. It should be noted, however, that there is large variation in the data. Half of the firms in our matched dataset have less than 702 employees and 421 million RMB in annual sales. On average, around 11% of the firms in our matched sample are at least 50% state owned, and 45% have positive sales outside of China. Finally, only 5.2% of matched firms in our data are publicly traded in the Chinese stock market.

4 Identification Strategy

In this section we describe our identification strategy. The objective of our empirical analysis is twofold. First, to identify the effect of the credit supply increase by Chinese banks during the stimulus years on firm borrowing, investment and size. Second, 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

changes generated by the stimulus plan. Similarly to Chodorow-Reich (2014), our identification strategy exploits variation in bank lending at national level during the stimulus years to construct a firm-specific measure of exposure to the credit increase generated by the stimulus plan.¹⁸ To this end, we construct the following measure of firm-level exposure to bank credit supply:

$$\Delta \widetilde{L}_{it} = \sum_{b \in O_i} \omega_{bi,t=0} \times \Delta \log L_{b-i,t} \quad , \quad (1)$$

where b , i , and t index banks, firms, and time respectively. The variable $\Delta \log L_{b-i,t}$ is the change in the logarithm of the aggregate loan balance of bank b between year $t - 1$ and t to all borrowers other than firm i . The weights $\omega_{bi,t=0}$ capture the strength of the relationship between firm i and bank b in the initial period.¹⁹ We define the weights as $\omega_{bi,t=0} = \frac{l_{bi,t=0}}{\sum_{b \in O_i} l_{bi,t=0}}$, i.e. outstanding loans of bank b to firm i divided by total outstanding loans to firm i from all banks with which firm i has a credit relationship (the set O_i), both observed in the pre-stimulus period.

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.²⁰ 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 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.

¹⁸This strategy is similar to a Bartik instrument (Bartik (1991)) largely used in the labor literature starting from Blanchard, Katz, Hall, and Eichenengreen (1992). See Greenstone, Mas, and Nguyen (2015) for an application to credit markets.

¹⁹In 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.

²⁰These 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).

4.1 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 $\Delta \widetilde{L}_{it}$ should not 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 age and size.

Table 3 reports the coefficient on $\Delta \log L_{b-i,t}$ when the outcome variable is lending of bank b to firm i . As shown, 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:

$$\Delta \log loan_{ibt} = \alpha + \alpha_{it} + \beta \Delta \log L_{b-i,t} + \varepsilon_{ibt} \quad (2)$$

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 reports 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 $\Delta \log L_{b-i,t}$ in both time periods are positive. Importantly, these estimates are of similar magnitude as the ones described above and obtained with the same specification but without the interaction of firm and time fixed effects. This is shown in 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.²¹ Therefore, the coefficients reported in Table 3 support the validity of our identification strategy.

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.

²¹The 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)).

5.1 The Effect of Credit Supply on Firm-Level Outcomes

5.1.1 Average Effect

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:

$$\Delta \log y_{ijct} = \alpha_j + \alpha_c + \alpha_t + \beta \Delta \widetilde{L}_{it} + \gamma X_{i,t-1} + \varepsilon_{ijct} \quad (3)$$

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 $\Delta \widetilde{L}_{it}$ 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.

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 in this table 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 including all firm controls – 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.

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 not only experienced larger increase 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 .23 percent larger increase in investment and .33 percent larger increase in employment.

5.1.2 Heterogeneous Effects

Next, we study in more detail the allocation of bank loans across firms during the stimulus years 2009 and 2010. To this end, we estimate the following version of equation (3):

$$\begin{aligned} \Delta \log y_{ijct} = & \alpha_j + \alpha_c + \alpha_t + \beta_1 \Delta \widetilde{L}_{it} \times C_{i,t-1} + \beta_2 \Delta \widetilde{L}_{it} + \beta_3 C_{i,t-1} \\ & + \gamma X_{i,t-1} + \varepsilon_{ijct} \end{aligned} \quad (4)$$

where the variable $C_{i,t-1}$ is a pre-determined firm characteristic and captures, depending on the specification, either the share of state-ownership of firm i or its initial average product of capital, both defined in the pre-stimulus period. The coefficient of interest is β_1 , which captures the differential effect of exposure to bank credit supply on firm-level outcomes depending on initial firm characteristics. As in Table 4, we focus on three main firm-level outcomes: change in firm borrowing, investment and employment growth.

We start by studying the effects of credit supply on firm-level outcomes for firms with different initial levels of state ownership. The results are reported in Table 5. In columns 1 and 2 the outcome variable is change in firm borrowing. The estimated coefficient β_1 is positive and significant in both specifications. This indicates that the effect of credit supply on firm borrowing is relatively larger for state-owned firms than for private firms during the stimulus years. The estimated coefficient β_2 is also positive and significant, which indicates that the differential effect on firm borrowing between state-owned and private firms is on top of a positive increase in private firms' borrowing. Taken together,

the magnitudes of the estimated β_1 and β_2 coefficients in column 2 – our preferred specification – indicate that, in response to a 1 standard deviation change in credit supply, fully state-owned firms experience an 15.7 percent increase in borrowing, versus the 11.5 percent increase for fully private firms. To sum up, during the stimulus years of 2009 and 2010, the effect of credit supply on firm borrowing was 36% larger for state-owned firms relative to private firms.²² In columns 3 to 6 we study the heterogeneous effects of credit increases on real outcomes for firms with different levels of state-ownership. Our results show that the credit increase during stimulus years translated into larger increase in employment for state-owned firms than private firms, but had very similar effects in terms of investment. The magnitude of the estimated coefficients in columns 4 and 6 – our preferred specification – indicate that in response to a 1 standard deviation change in credit supply, private firms experienced a 2.7 percent increase in investment and 2.9 percent increase in employment. For the same increase in credit supply, fully state-owned firms increased investment at the same rate as private firms but experienced a 12.4 percent increase in employment, four times the increase of private firms.

Next, we study the effects of credit supply increases on firm-level outcomes for firms with different initial levels of average product of capital (*APK*). Table 6 report the results of estimating equation (4) when C_{icjt-1} is equal to the firm-level *APK* in the pre-stimulus period. The average product of capital is defined as the log of industrial value added divided by book value of fixed assets and is used here as a proxy for marginal product of capital. In columns 1 and 2 the outcome variable is change in firm borrowing. The estimated coefficient on the interaction between credit supply increases and initial average product of capital is negative. This indicates that, during the stimulus years, the effect of credit supply on firm borrowing was larger for firms with lower pre-stimulus marginal product of capital. The magnitude of the estimated coefficient β_1 indicates that firms with a 1 standard deviation larger *APK* experienced a 8 percent lower increase in bank loans during the 2009-2010 period. This result suggests an increase in credit misallocation

²²A caveat is in order in reading these magnitudes. Our data does not cover entrusted loans that Chinese firms can make to each other. For example, if SOE firms in this period were lending to private firms through entrusted loans, the magnitude of the heterogeneous effects presented above would be in part mitigated.

during stimulus years. In addition, it is consistent with state-owned firms experiencing a relatively larger increase in new loans during the stimulus years with respect to private firms. Next, we study heterogeneous effects on real firm-level outcomes. Columns 3 and 4 show that, despite receiving less credit, firms with higher initial APK have a higher elasticity of investment to bank loans. This is consistent with our measure of APK being a good proxy for marginal product of capital (MPK), which also follows from our model with Cobb-Douglas production function presented in section 6. Finally, in columns 5 and 6, we find no heterogeneous effects on employment growth for firms with different initial APK .

5.1.3 Credit Allocation: Before, During and After Stimulus

In this section we apply our identification strategy to time periods outside of the stimulus years. In particular, we are interested in studying whether the heterogeneous effects of credit supply on firm borrowing between state-owned and private firms are specific of the stimulus plan years or are a more general feature of the Chinese banking sector. To this end, we estimate equation 4 separately for three different periods: the pre-stimulus years 2006 to 2008, the stimulus years 2009 and 2010, and the post stimulus years 2011 to 2013.

Table 7 reports the results. Because we are interested in studying how credit allocation across firms might have changed over time, the main outcome variable of interest in this table is firm borrowing. Columns 1 and 2 report the coefficients obtained estimating equation 4 in the pre-stimulus period. The coefficient on the interaction between credit supply increases and state-ownership is negative and strongly significant in the pre-stimulus years. This indicates that, up to 2008, higher credit supply had a larger effect on firm borrowing for private firms relative to state-owned firms. We can quantify these coefficients in the same way as in Table 5. The magnitude of the estimates in column 2 indicates, in response to a 1 standard deviation change in credit supply, state-owned firms experience an 10.8 percent increase in borrowing, versus the 16.5 percent increase for private firms. This means that, in the pre-stimulus period, the effect of credit supply

on firm borrowing was 53% larger for private firms relative to state-owned firms. This result is consistent with the process of capital reallocation from low-productivity SOEs to high-productivity private firms that has been described as one of the driving forces of China's growth in the 2000s.

Columns 3 and 4 report the coefficients obtained estimating equation 4 in the stimulus period. These results have been already presented in columns 1 and 2 of Table 5 and are reported here for the reader's convenience. There are two important aspects to underline. First, the coefficient on the interaction between state ownership and credit supply increases changed sign after the introduction of the stimulus program. Second, the change in the trend of credit allocation between private and state-owned firms did not reverse back at the end of the stimulus years. Despite not statistically significant at standard levels, the coefficient on the interaction between state ownership and credit supply remains positive in the post-stimulus years, as shown in columns 5 and 6 of Table 7, suggesting that the effect of the stimulus plan on credit allocation extended outside of the 2009-2010 period.

6 A Dynamic Model of Transitional Economy

This section develops a dynamic model to illustrate how financial frictions affect credit allocation across firms. Our model builds on Song et al. (2011), but instead of focusing on the buildup of foreign surplus during economic transition, we focus on credit expansion in a time-varying and uncertain economic environment.

6.1 Setup and Assumptions

Time is discrete and infinite. There are two types of firms in each period, both requiring capital and labor to operate. A unit measure of state-owned or state-connected enterprises (S firms) operate as standard neo-classical firms and, as discussed in more details 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,

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

where y , k , and n are output, capital, and labor, respectively. Capital fully depreciates and firms shut down after each period. $\tilde{A}_{S,t} = A_t$ with probability 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.²³ We set N_t to be a constant to focus on the labor share dynamics and illustrate key mechanisms.²⁴

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 R_S in the next period, or a private fund that invests in a diversified portfolio of private

²³Song 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”.

²⁴Population growth and demographic changes can be easily incorporated, but are less prominent around the stimulus period and do not add to our economic insight.

enterprises that operate the next period.²⁵ 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.²⁶ 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.²⁷ $\delta = \frac{\mu}{\mu + (1 - \mu)b}$ captures how much S firms are differentially favored in terms of interest rates or cost of capital (the *interest rate friction*).²⁸

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

²⁵We 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).

²⁶In reality, Q_t is time-varying post-stimulus and the stimulus could have been anticipated. This is not crucial to our results.

²⁷Implicit bailout is also the driver in Chang, Liu, Spiegel, and Zhang (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.

²⁸A revealing example of selective bail-out by the Chinese government is the case of China Eastern and East Star Airlines. The former is a state-owned enterprise while the latter is privately owned. Both airlines were in financial distress at the beginning of 2009. China Eastern obtained a capital injection of 7 billion 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 and was declared bankrupt in August 2009.

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). 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.

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.

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.²⁹

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

²⁹According to Steinfeld (2000); Kornai, Maskin, and Roland (2003), the arrangement of having state-directed banks lending to money-losing SOEs is common in command economies that attempted to liberalize. These banks were periodically bailed out themselves when bad loans surfaced, perpetuating the problem of such soft loans.

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.³⁰

6.2 Dynamic Equilibrium

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

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

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

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

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

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

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

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

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

³⁰We only need there to be sufficient capital in the economy to ensure this. Note that because that the entrepreneurs face the same risk of company failure as workers and as managers, risk aversion does not matter for this decision.

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:

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

where $m_t = (1 - \eta B_t)\rho_t k_t$ is his or her total payoff in period t , and B_t is an indicator of whether the pledgeability 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

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

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:

$$\underbrace{Q_t}_{\text{Credit Supply}} = \underbrace{l_{S,t} + l_{P,t}}_{\text{Credit Supply}} = \underbrace{k_{P,t} + k_{S,t} - s_{P,t}}_{\text{Credit Demand}} \quad (5)$$

$$N_t = n_{P,t} + n_{S,t} = \frac{\chi^{\frac{1-\alpha}{\alpha}} k_{P,t} + k_{S,t}}{A_t} \left(\frac{R_{S,t}}{\alpha} \right)^{\frac{1}{1-\alpha}} \quad (6)$$

6.3 Discussion and Implications

Reallocation of Capital and Labor

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

$$1 + \gamma_t = \frac{k_{P,t}}{k_{P,t-1}} = \frac{\psi_t}{(1 - \eta B_t) \rho_t \mu_t} \frac{s_{P,t}^*}{k_{P,t-1}} = \phi \frac{\mu_{t-1} \rho_{t-1}}{\mu_t \rho_t} \tilde{\psi}_t (1 + \beta^{-\theta} ((1 - \phi) \psi_t)^{1-\theta})^{-1} \quad (7)$$

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 (7) 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 .³¹ 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.³² Similarly, we note $\frac{\partial(1+\gamma_t)}{\partial \mu} > 0$ because ψ and $\frac{\psi_t}{\rho_t}$ 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 Table 5. In particular, credit increase during stimulus years had a larger impact on firm borrowing and employment for state-owned firms than for private firms.

³¹As 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.

³²In 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.

Finally, we illustrate these predictions of the model in terms of credit share of S firms in Figure 6 (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 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 Table 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 columns 5 and 6 in Table 7 discussed earlier, and can have significant cumulative impact on real outputs and economic growth.

7 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 in-

creasing 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. We also 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 evidence suggests that the reversal helped preserving employment but at the expense of facilitating productive investment and long-run growth.

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

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Figures and Tables

Figure 1: Structure of China Economic Stimulus Plan

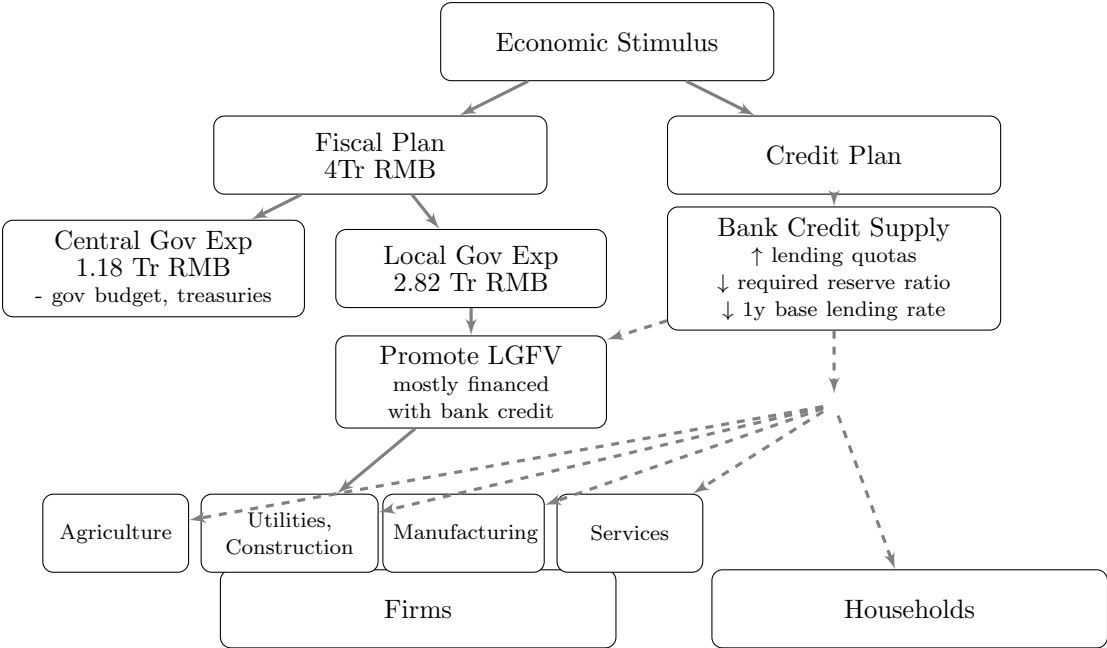
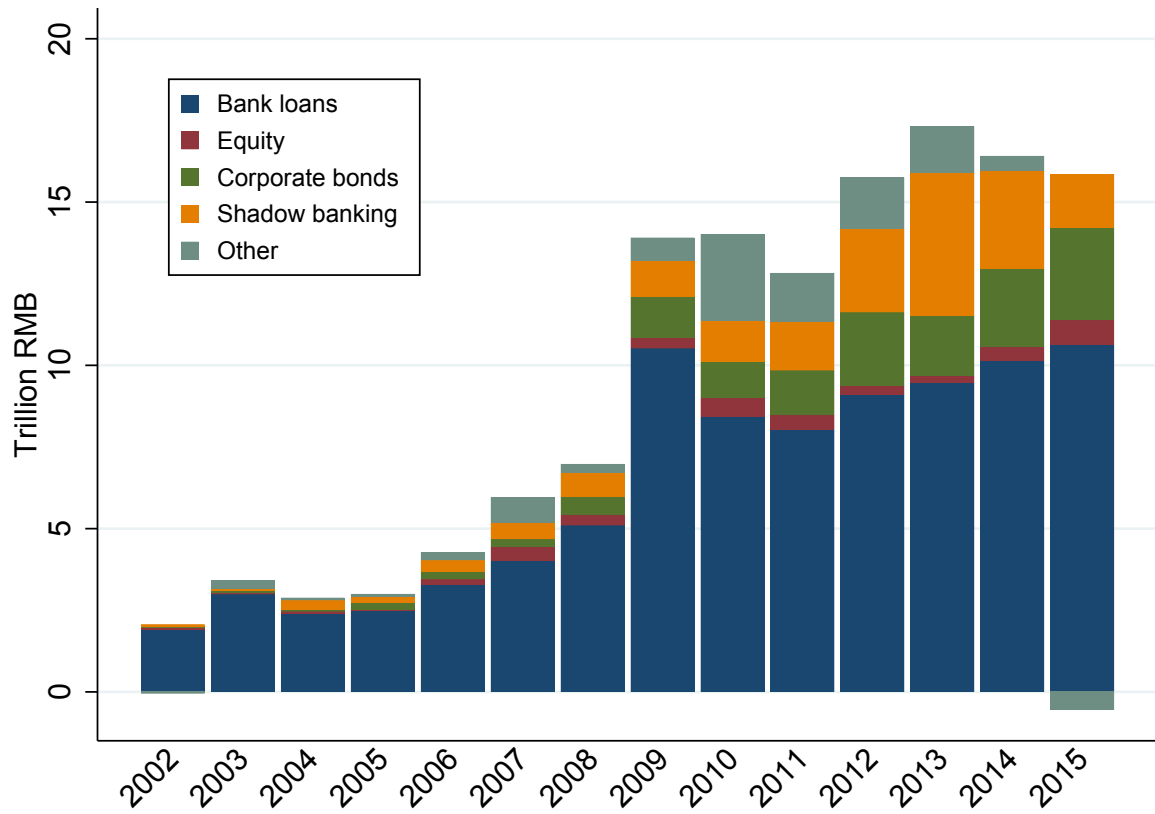
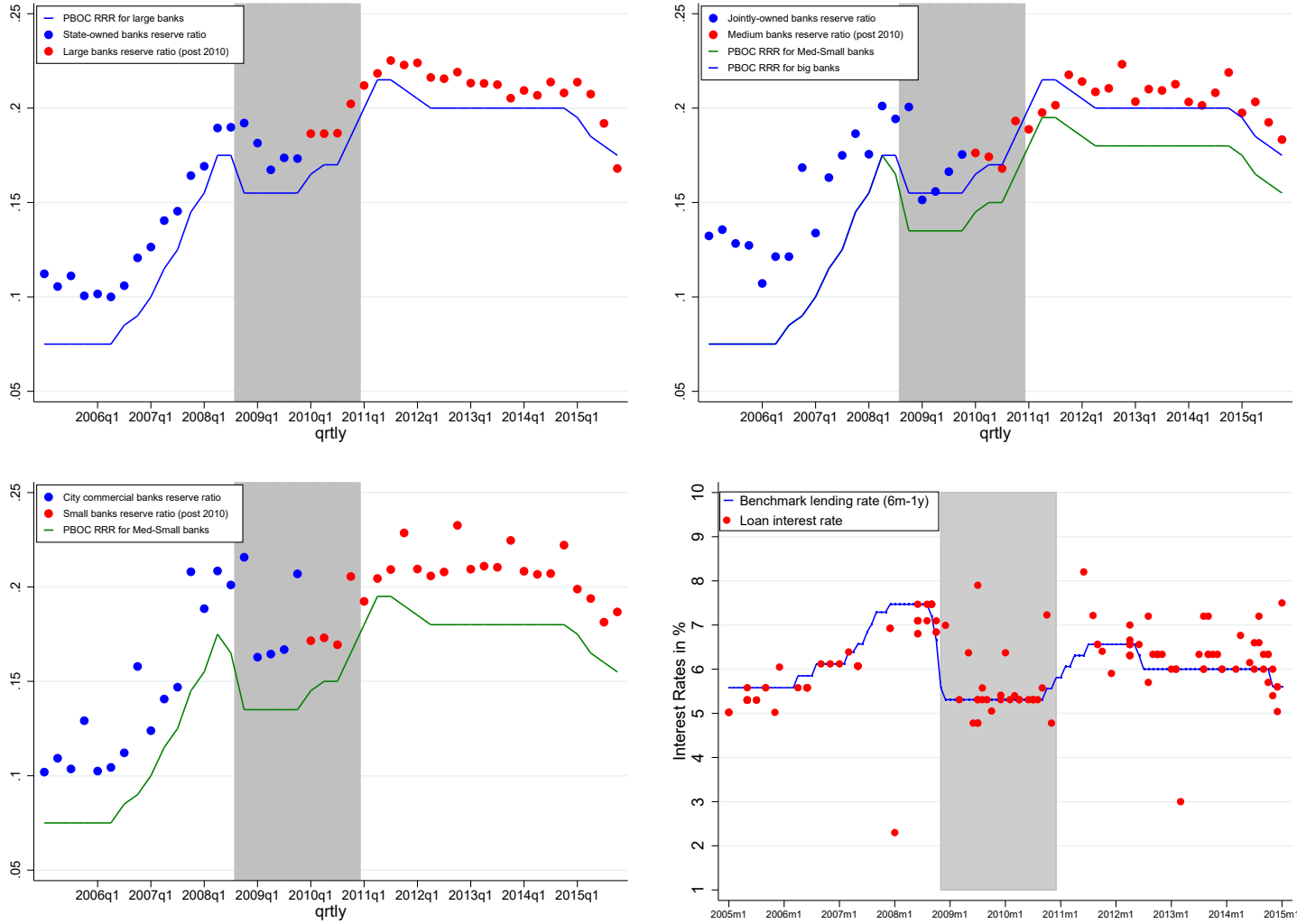


Figure 2: Aggregate Financing to the Real Economy



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.

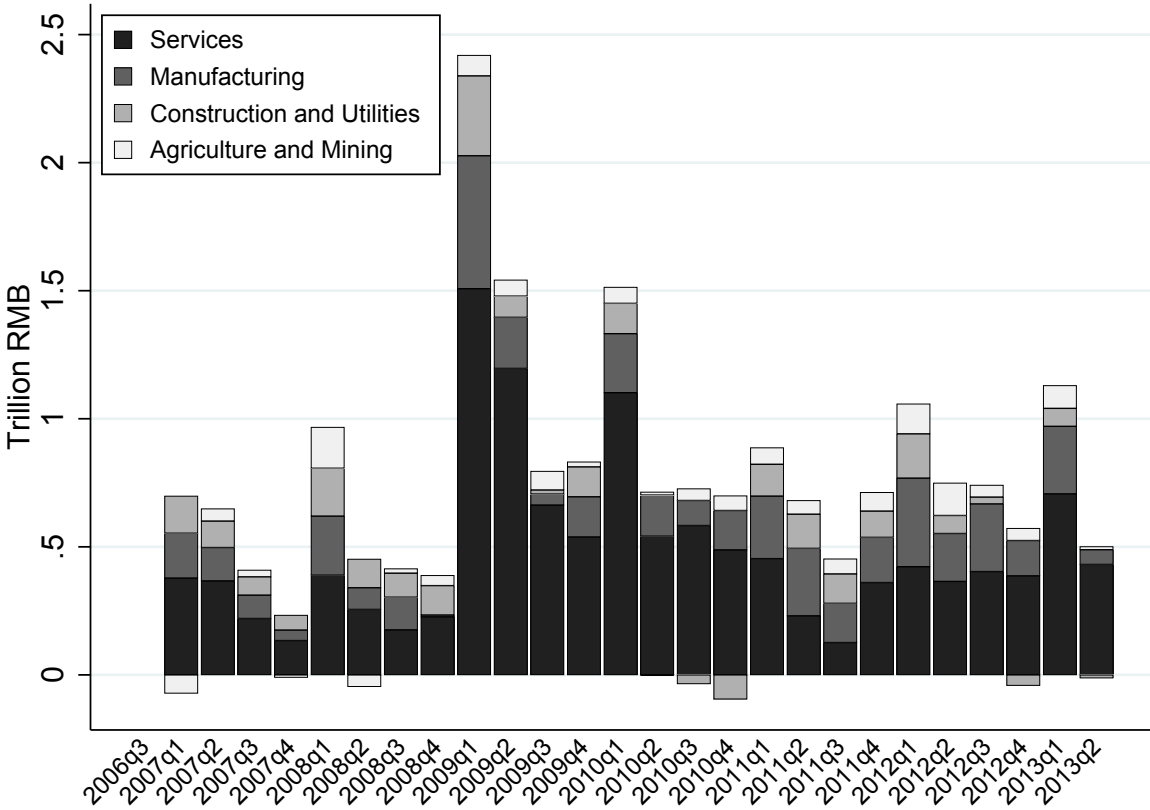
**Figure 3: Changes in Banking Regulation during Stimulus Years:
Bank Required Reserve Ratio (RRR) and Benchmark Lending Rate**



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.

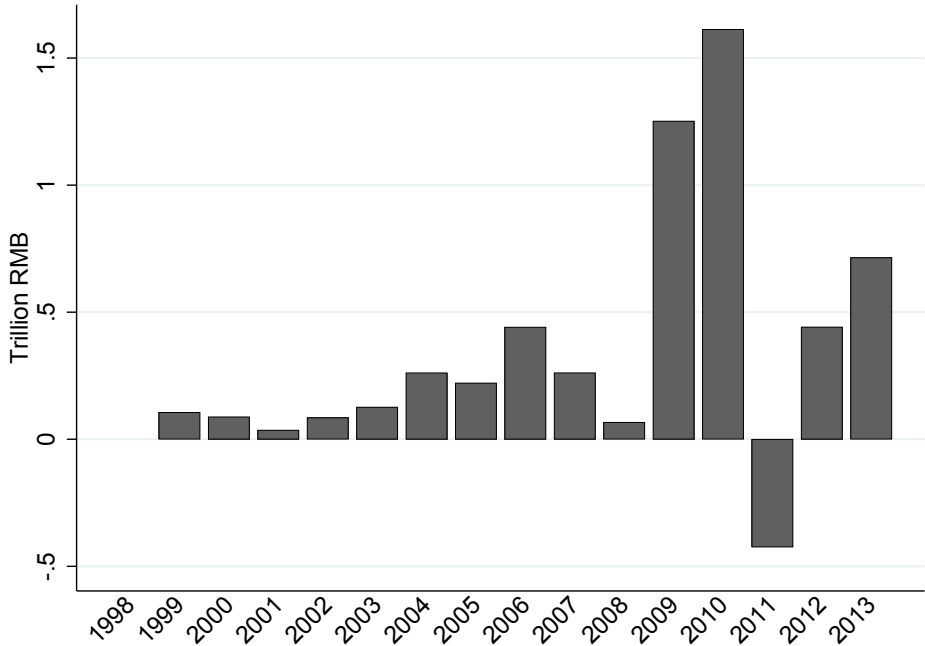
Figure 4: Bank Lending to Firms - by Sector

Quarterly data, 2007-2013



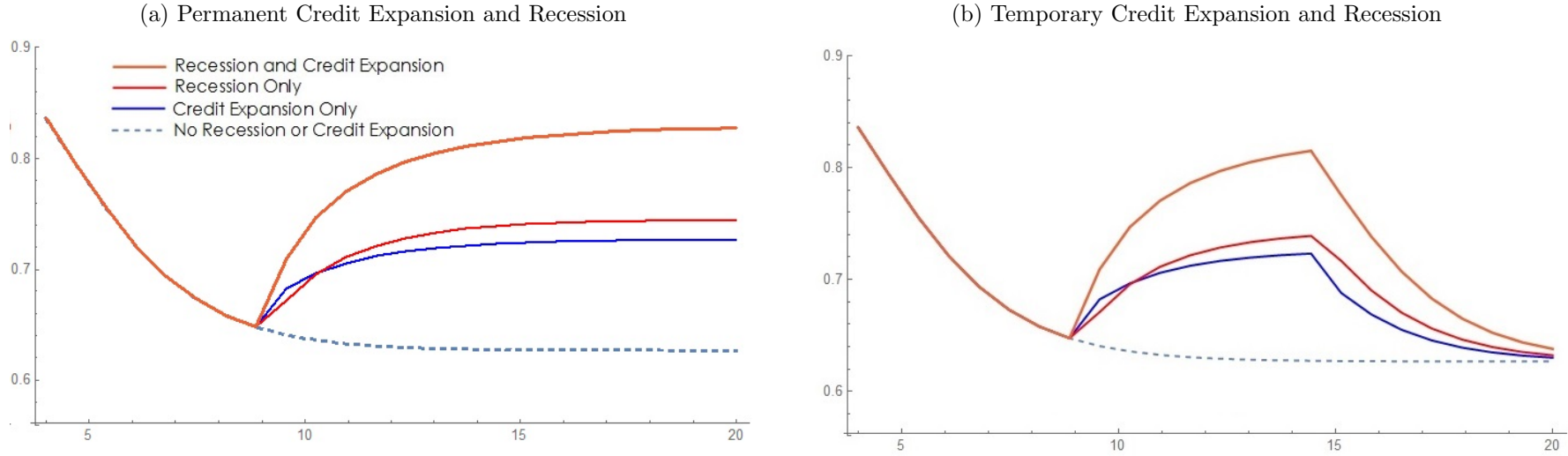
Notes: Source: China Banking Regulatory Commission. To produce this graph we first sum across firms the monetary value of their outstanding loan balance at the end of each quarter. Then we take a quarter to quarter difference of the sum.

Figure 5: 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 6: Dynamics of Resource Allocation:
Shares of Bank Credit to S Firms**



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 $\mu = 0.91$).

Table 1: Summary Statistics

Variable Name	Mean	Median	St.Dev.	N
Panel A: CBRC loan-level data:				
<i>loan_{ibt}</i> (million RMB)				
all years	163	63	452	177,087
stimulus years	179	68	474	39,005
stimulus years, firm-level	554	156	1791	11,067
$\Delta \log loan_{ibt}$				
all years	0.039	0.000	0.433	177,087
stimulus years	0.033	0.000	0.461	39,005
stimulus years, firm-level ($\Delta \log loan_{it}$)	0.094	0.048	0.442	11,067
Panel B: Annual Survey of Industrial firms:				
number of employees	2,144	702	7,405	11,067
fixed assets (thousand RMB)	731,427	120,996	3,698,826	11,067
sales (thousand RMB)	1,621,470	421,214	6,255,161	11,067
<i>StateShare</i>	0.113	0.000	0.290	11,067
$I(StateShare > 0.5)$	0.111	0.000	0.315	11,067
age (year)	15	11	14	11,067
exporter dummy	0.449	0.000	0.497	11,067
public	0.052	0.000	0.222	11,067
$\Delta \log$ employment	0.027	0.045	0.598	11,067
$\Delta \log$ fixed assets	-0.272	-0.073	0.669	11,067
Panel C: independent variables:				
$\Delta \log L_{b-i,t}$				
all years	0.131	0.118	0.113	177,087
stimulus years	0.231	0.187	0.127	39,005
$\Delta \widetilde{L}_{it}$	0.219	0.198	0.115	11,067

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: sample:	New loan from lender $_{bi,t}$	
	all years (1)	stimulus years (2)
Pre-existing banking relationship	0.949 [0.001]***	0.941 [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)
$\Delta \log Loans_{b-i,t}$	0.173 [0.045]***	0.174 [0.045]***	0.161 [0.048]***	0.189 [0.058]***	0.166 [0.066]**	0.166 [0.066]**	0.170 [0.075]**	0.193 [0.089]**
Year FE	y	y	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 \times Year FE				y				y
R-squared	0.012	0.012	0.012	0.341	0.026	0.027	0.030	0.350
Observations	177,087	177,087	143,525	143,525	39,005	39,005	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:	$\Delta \log loan_{it}$		$\Delta \log K_{it}$		$\Delta \log L_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \widetilde{L}_{it}$	1.041 [0.088]***	1.036 [0.088]***	0.242 [0.105]**	0.225 [0.107]**	0.352 [0.100]***	0.329 [0.098]***
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	0.095	0.435	0.438	0.226	0.232
Observations	11,067	11,067	11,067	11,067	11,067	11,067

Notes: The unit of observation is a firm. The dependent variables are: the yearly change in the log of total outstanding bank loan balance, the yearly change in the log of book value of total fixed assets, the yearly change in the log of average number of workers. 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 on Firm-level outcomes
Heterogeneous Initial State-Ownership. Stimulus Years (2009-2010)**

outcome:	$\Delta \log loan_{it}$		$\Delta \log K_{it}$		$\Delta \log L_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \widetilde{L}_{it}$	1.008 [0.087]***	1.002 [0.087]***	0.248 [0.107]**	0.231 [0.109]**	0.276 [0.101]***	0.253 [0.100]**
$\Delta \widetilde{L}_{it} \times StateShare_{i,t-1}$	0.365 [0.118]***	0.365 [0.118]***	-0.061 [0.203]	-0.070 [0.203]	0.829 [0.250]***	0.822 [0.251]***
$StateShare_{i,t-1}$	-0.084 [0.026]***	-0.078 [0.026]***	0.034 [0.043]	0.048 [0.043]	-0.181 [0.056]***	-0.167 [0.055]***
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	0.093	0.095	0.435	0.438	0.228	0.234
Observations	11,067	11,067	11,067	11,067	11,067	11,067

Notes: The unit of observation is a firm. The dependent variables are: the yearly change in the log of total outstanding bank loan balance, the yearly change in the log of book value of total fixed assets, the yearly change in the log of average number of workers. 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: Heterogeneous Effects of Bank Credit Supply on Firm-level outcomes
Heterogeneous Initial Average Product of Capital. Stimulus Years (2009-2010)**

outcome:	$\Delta \log loan_{it}$		$\Delta \log K_{it}$		$\Delta \log L_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \widetilde{L}_{it}$	1.024 [0.091]***	1.015 [0.091]***	0.377 [0.113]***	0.363 [0.115]***	0.359 [0.106]***	0.337 [0.104]***
$\Delta \widetilde{L}_{it} \times \log APK_{i,t=1}$	-0.058 [0.027]**	-0.059 [0.027]**	0.360 [0.063]***	0.361 [0.063]***	0.018 [0.080]	0.020 [0.080]
$\log APK_{i,t=1}$	0.047 [0.008]***	0.047 [0.008]***	-0.096 [0.015]***	-0.091 [0.015]***	-0.003 [0.019]	0.006 [0.019]
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	0.098	0.100	0.441	0.444	0.226	0.232
Observations	11,067	11,067	11,067	11,067	11,067	11,067

Notes: The unit of observation is a firm. The dependent variables are: the yearly change in the log of total outstanding bank loan balance, the yearly change in the log of book value of total fixed assets, the yearly change in the log of average number of workers. 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: The Effect of Bank Credit Supply on Loans
Credit Allocation: Before, During and After Stimulus**

outcome:	$\Delta \log loan_{it}$					
	pre-stimulus		stimulus		post-stimulus	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \widetilde{L}_{it}$	1.407 [0.092]***	1.431 [0.093]***	1.008 [0.087]***	1.002 [0.087]***	1.564 [0.124]***	1.527 [0.126]***
$\Delta \widetilde{L}_{it} \times StateShare_{i,t=0}$	-0.494 [0.226]**	-0.494 [0.222]**	0.365 [0.118]***	0.365 [0.118]***	0.189 [0.198]	0.225 [0.198]
$StateShare_{i,t=0}$	0.066 [0.044]	0.067 [0.044]	-0.084 [0.026]***	-0.078 [0.026]***	-0.009 [0.020]	-0.001 [0.019]
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	0.089	0.095	0.093	0.095	0.072	0.074
Observations	12,540	12,540	11,067	11,067	22,947	22,947

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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.